FORECASTING ELECTRICITY CONSUMPTION:

A Comparison of Growth Curves, Econometric and ARIMA Models for Selected Countries and World Regions

Zaid Mohamed

B.E. (Hons)

A thesis presented for the degree of
Doctor of Philosophy
in
Electrical and Electronic Engineering
at the
University of Canterbury,
Christchurch, New Zealand

November 2004

UNIVERSITY OF CANTERBURY
Te Whare Wānanga o Waitaha
CHRISTCHURCH NEW ZEALAND

Dedicated to my loving daughter Zaamaa, caring wife Shamila,

and dear parents, brothers and sisters

ABSTRACT

This thesis presents six forecasting models for annual electricity consumption based on various time series extrapolation techniques. The proposed models are based on growth curves, multiple linear regression analysis using economic and demographic variables (referred to as the Combined model) and autoregressive integrated moving average (ARIMA) techniques. The proposed models are applied to electricity consumption data of New Zealand, the Maldives, the United States of America and the United Kingdom. The models are also applied to the electricity consumption data of various world regions and the world total, and are compared using model fit and forecasting accuracies.

This thesis initially investigates the patterns of electricity consumption to study the link between electricity consumption, economic growth and population. Although the link between economic growth and electricity consumption varies between developing and industrialised countries, the link is strong enough to justify the use of these variables in the models of all countries and regions. In addition, the patterns appear uninfluenced by the adoption of regulatory or market type economies, suggesting that the forecasts of the proposed models should not be affected during the period of regulatory reforms in the electricity industry.

In general, application of the models at the country level revealed that the simple Harvey model, based on a growth curve, has performed better than the more complex ARIMA and regression models. For the regional and world total electricity consumptions, the ARIMA models are the best followed very closely by the regression and Harvey models. However, Harvey is the only model that gave among the best forecasts in the short, medium and long term forecasting. Overall, it was concluded that the simple Harvey model performed better than or as good as the more complex ARIMA and Combined models. In general, the Harvey model is the best in forecasting mature electricity industries when more data points are available, the ARIMA model is the best when the number of data points available is limited and the Combined model always gave average results for all data sets.

LIST OF PUBLICATIONS

The following papers have either been published, accepted for publication or submitted during the course of the research described in this thesis:

1. Mohamed, Z., and Bodger, P.S., Analysis of the Logistic model for predicting New Zealand electricity consumption, *Proceedings of the Electricity Engineer's Association (EEA) of New Zealand 2003 Conference*, EEA Annual Conference & Trade Exhibition, Christchurch, NZ, 20-21 June 2003.

2. Mohamed, Z., and Bodger, P.S., A comparison of Logistic and Harvey models for electricity consumption in New Zealand, *Technological Forecasting and Social Change*, Accepted for publication, May 2004, Currently available online at www.sciencedirect.com

3. Mohamed, Z., and Bodger, P.S., Forecasting electricity consumption: A comparison of models for New Zealand, *Proceedings of the Electricity Engineer's Association (EEA) of New Zealand 2004 Conference*, EEA Annual Conference & Trade Exhibition, Christchurch, NZ, 17-19 June 2004.

4. Mohamed, Z., and Bodger, P.S., Forecasting electricity consumption in New Zealand using economic and demographic variables, *Energy*, Vol. 30, Issue 10, pp. 1833-1843, 2005.

5. Mohamed, Z., and Bodger, P.S., A variable asymptote logistic (VAL) model to forecast electricity consumption, *International Journal of Computer Applications in Technology (IJCAT)*, Vol. 22, Nos. 2/3, pp. 65-72, 2005.

6. Mohamed, Z., and Bodger, P.S., Forecasting electricity consumption: A comparison of models for New Zealand, *Proceedings of the Australasian*

Universities Power Engineering Conference (AUPEC) 2004, Paper 32, Brisbane, 16-29 September 2004.

7. Mohamed, Z., Bodger, P.S., and Hume, D.J., Forecasting electricity consumption: A comparison of models for New Zealand and the Maldives, *Proceedings of the International Conference on Power Systems (ICPS) 2004*, Vol. 2, pp. 613 - 618, Kathmandu, Nepal, 3-5 November 2004.

8. Bodger, P.S., and Mohamed, Z., World, regional, country and New Zealand electricity patterns, Invited presentation at *The Royal Society of New Zealand Annual Conference 2004*, Christchurch, New Zealand, 18 November 2004.

9. Mohamed, Z., and Bodger, P.S., Forecasting electricity consumption : A comparison of growth curves, regression and ARIMA techniques, Presentation to the *New Zealand Energy Modelling Workshop #1*, held at Victoria University, New Zealand on 20 October 2004., [Filename: emw_1_2004_mohamed.pdf], Webpage: http://www.mcs.vuw.ac.nz/events/EMW/, 2004.

10. Mohamed, Z., and Bodger, P.S., A comparison of electricity forecasting models for New Zealand, Paper submitted and in review for publication in *International Journal of Electrical Power & Energy Systems*, June 2004.

11. Mohamed, Z., and Bodger, P.S., A comparison of electricity forecasting models for New Zealand, United States, United Kingdom and Maldives, Paper submitted and in review for publication in *Technological Forecasting and Social Change*, June 2004.

ACKNOWLEDGEMENTS

I would like to thank my supervisor Professor Pat Bodger for his constant encouragement, valuable guidance, support and advice during the course of this research. I would also like to thank him for the various financial support he has provided during this work. I could not have done this without you. I really appreciate that and would like to say "*Shukuriyya*" (Thank you).

I would like to take this opportunity to thank my parents for their tremendous mental and financial support. Clearly this could not have been possible if my dear parents had not taken the decision to educate me and my family by bringing us to the capital island Male' (Maldives) at a time when the people in our island were not very aware of the importance of providing modern education to their children. I would also like to thank all my brothers and sisters especially my elder brother and friend '*Thuthu*' who convinced me that I could come this far, and has been a constant inspiration to my education from very early childhood to this date. Thanks also go to the other members of my family and friends who have supported me in my education. I love you all and thanks for being there.

I would like to thank my colleagues in Room 310 for their help, especially to Chris Collins, Ross Halliday and Dr. David Hume. I am very pleased to be part of the electric power engineering research group of this department. I would also like to thank my friend Dr. Arif Mohamed for his helpful suggestions during the final stages of writing. Thanks to Dr. Aminath Laafira and Dr. Muhammed Musa for their comments. A big thank you to all the friends from my country here in New Zealand who have accompanied me and made me feel at home during my stay here.

I would like to thank the New Zealand Agency for International Development (NZAID) for offering me a Postgraduate Scholarship for over 2 years. I would also like to thank the State Electric Company Limited (STELCO), Maldives, for their support in completing this degree. I could not have completed this work without the huge financial support from my hard working father and mother especially during the latter part of my work.

Last but not the least, I would like to thank my loving wife Shamila for her love, patience, sacrifice and support. You have sacrificed very important times of your life to be here with me and to support me. Thank you for taking such good care of our daughter Zaamaa. I appreciate the lonely hours you have spent at home while I was working at the university for long hours. Finally, a big hug and kiss to my loving daughter who says "bye bye" unwillingly when I leave to university and is excited every time I come home. The love and company the two of you have provided have been a constant moral support for this work.

CONTENTS

ABSTRACT v

LIST OF PUBLICATIONS vii

ACKNOWLEDGEMENTS ix

LIST OF FIGURES xxi

LIST OF TABLES xxix

CHAPTER 1 INTRODUCTION 1

1.1 General 1
1.2 Thesis Objectives 2
1.3 Thesis Outline 7

CHAPTER 2 ELECTRICITY PATTERNS AND DEREGULATION 9

2.1 Introduction 9
2. 2 Definitions 13
2.2.1 Electricity Intensity 13
2.2.2 Electricity Intensity Curve 13
2.2.3 Electricity Intensity Factor 14
2.3 Intensity in Selected Countries 15
2.3.1 Results 15
2.3.2 Discussion 23
2.3.2.1 Intensity in China *24*
2.3.2.2 Intensity in India *26*
2.3.2.3 International Level Comparisons *27*

2.4 Intensity in the Regions 30
2.4.1 Results 30
2.4.2 Discussion of Results 36
2.5 Deregulation and Privatisation of Electricity 39
2.5.1 Underlying Factors for Restructuring of Electric Power Industry 40
2.5.2 Historical Trends towards Privatisation 41
2.5.2.1 New Zealand 41
2.5.2.2 United States 41
2.5.2.3 United Kingdom 42
2.5.3.4 Maldives 42
2.5.2.5 China 42
2.5.2.6 Japan 43
2.5.2.7 Russia 43
2.5.2.8 Germany 43
2.5.2.9 France 44
2.5.2.10 India 44
2.5.2.11 Indonesia 44
2.5.2.12 Brazil 45
2.5.3 Impacts of Privatisation 45
2.6 Electricity Intensity, Deregulation and Electricity Consumption 48
2.7 Summary 50

CHAPTER 3 STATISTICAL TESTS FOR FORECASTING MODELS 53

3.1 Introduction 53
3.2 Autocorrelation Analysis 53
3.3 Coefficient of Determination 54
3.4 F-test 55
3.5 T-test 56
3.6 Durbin-Watson Statistic 56
3.7 Autocorrelation and Partial Autocorrelation Plots 57
3.8 Portmanteau Tests 58
3.9 Accuracy Measures 59
3.10 Summary 60

CHAPTER 4 ELECTRICITY FORECASTING MODELS **61**

4.1 Introduction 61

4.2 The Logistic model 61

4.2.1 Background 61

4.2.2 The Logistic Growth Curve 64

4.2.2.1 Pearl's Biological Growth Curve *64*

4.2.2.2 A Technological Substitution Model *65*

4.2.2.3 Modelling the Rate of Imitation *66*

4.2.2.4 The Logistic Model *66*

4.2.3 Logistic Curve Fitting Technique 68

4.2.3.1 Estimating the Upper Limit *68*

4.2.3.2 Fibonacci Search Technique *69*

4.3 Econometric Models 72

4.3.1 Background 72

4.3.2 The Regression Equation as a Forecasting Model 73

4.3.2.1 Simple Regression as a Model *73*

4.3.2.2 Multiple Linear Regression as a Model *76*

4.4 Box Jenkins ARIMA Models 78

4.4.1 Background 78

4.4.2 Forecasting Using ARIMA Models 79

4.4.2.1 Analysis of Time Series for Stationarity *80*

4.4.2.2 Differencing *81*

4.4.2.3 Identifying ARIMA Models *83*

4.4.2.4 Parameter Estimation *84*

4.4.2.5 Diagnostic Checking of Residuals *86*

4.5 Harvey Logistic and Harvey models 86

4.5.1 Background 86

4.5.2 Harvey Logistic Model 87

4.5.3 Harvey Model 89

4.6 Variable Asymptote Logistic (VAL) Model 90

4.6.1 Background 90

4.6.2 Variable Asymptote Logistic Approach 91

4.6.2.1 Proposed Model *91*

4.6.2.2 Estimation of Saturation Level *92*

4.6.2.3 Re-estimation of the Saturation Level *93*

4.6.2.4 VAL Method and Forecasting ... 94
4.7 Summary ... 95

CHAPTER 5 ELECTRICITY INDUSTRY IN NEW ZEALAND ... 97

5.1 Introduction ... 97
5.2 The Early Days of Electricity ... 98
5.3 The Initial Role Played by the Government ... 100
5.4 Towards a System of Electricity ... 102
5.5 Electricity Development in the North Island ... 103
5.6 Electricity Development in the South Island ... 105
5.7 Planning for Demand of Electricity ... 106
5.8 Thermal Generation of Electricity ... 110
5.9 Geothermal Generation of Electricity ... 112
5.10 ECNZ and Issues of Efficiency ... 113
5.11 Corporatisation and Break-up of ECNZ ... 115
5.12 Recent Changes of the Electricity Industry ... 118
5.13 Summary ... 119

CHAPTER 6 APPLICATION OF THE MODELS TO NEW ZEALAND ... 121

6.1 Introduction ... 121
6.2 Electricity Consumption in New Zealand ... 122
6.3 Application of the Logistic Model ... 123
6.3.1 Autocorrelation Analysis ... 123
6.3.2 Application to Electricity Consumption ... 124
6.3.3 Comparison with Historical Forecasts ... 127
6.3.4 Effect of Historical Data on the Asymptotic Value ... 130
6.4 Econometric Models for New Zealand ... 134
6.4.1 Linear Models Based on Gross Domestic Product ... 134
6.4.1.1 Current GDP Model ... 135
6.4.1.2 Real GDP Model ... 141
6.4.2 Linear Model Based on Electricity Price ... 148
6.4.2.1 Current Price Model ... 148

6.4.3 Combined Model ... 153
6.4.4 Comparison of the Econometric Models ... 158
6.5 ARIMA Models ... 159
6.5.1 Domestic ARIMA Model ... 160
6.5.2 Non-Domestic ARIMA Model ... 163
6.5.3 ARIMA Model for Total Consumption ... 168
6.6 Harvey Logistic and Harvey Models ... 172
6.6.1 Harvey Logistic Model ... 173
6.6.2 Harvey Model ... 175
6.7 Variable Asymptote Logistic (VAL) Model ... 176
6.7.1 Initial Estimation of Saturation Levels ... 176
6.7.2 Correlation and Re-estimation of F ... 177
6.7.3 VAL Method and Forecasting ... 180
6.7.4 Model Selection using Forecasting Accuracy ... 180
6.7.5 Proposed VAL Model for New Zealand ... 182
6.7.6 Comparison with the Logistic Model ... 184
6.8 Comparison of Models ... 186
6.8.1 Model Fit and Forecasting Accuracy ... 186
6.8.1.1 Domestic Sector ... 187
6.8.1.2 Non-Domestic Sector ... 188
6.8.1.3 Total Consumption ... 188
6.8.2 Comparison of Forecasts ... 189
6.9 Summary ... 192

CHAPTER 7 FORECASTING ELECTRICITY IN THE MALDIVES ... 193

7.1 Introduction ... 193
7.2 Electricity Consumption in Male' ... 194
7.2.1 History of Electricity Development ... 194
7.2.2 Electricity Consumption ... 195
7.3 The Logistic Model ... 196
7.4 The Combined Model ... 196
7.5 Harvey Logistic and Harvey Models ... 199
7.6 ARIMA Models ... 202
7.6.1 ARIMA Model for the Domestic Sector ... 202

7.6.2 ARIMA Model for the Non-Domestic Sector 205
7.6.3 ARIMA Model for the Total Consumption 209
7.7 Application of the VAL Model to Male' 213
7.8 Comparison of Model Fit and Forecasting Accuracy 216
7.9 Comparison of Forecasts 219
7.10 Summary 221

CHAPTER 8 FORECASTING ELECTRICITY CONSUMPTION IN THE UNITED STATES OF AMERICA 223

8.1 Introduction 223
8.2 Overview of Electricity Development 224
8.3 Historical Electricity Consumption 225
8.4 The Logistic Model 226
8.5 The Combined Model 227
8.6 ARIMA Models 231
8.6.1 Domestic ARIMA Model 231
8.6.2 Non-Domestic ARIMA Model 234
8.6.3 ARIMA Model for the Total Electricity Consumption 237
8.7 Harvey Logistic and Harvey Models 240
8.8 The VAL Model 242
8.8.1 Fibonacci Search Technique 242
8.8.2 Re-estimation of the Saturation Level 243
8.8.3 Choice of VAL Model 244
8.8.4 VAL Model Forecasts 246
8.9 Comparison of the Models 247
8.9.1 Comparison of Model Fit and Forecasting Accuracy 247
8.9.2 Comparison of Forecasts 250
8.10 Summary 253

CHAPTER 9 FORECASTING ELECTRICITY CONSUMPTION IN THE UNITED KINGDOM 255

9.1 Introduction 255
9.2 Electricity Industry in the United Kingdom 256
9.2.1 Structure Prior to Privatisation 256
9.2.2 Privatisation and Current Structure 256
9.2.3 Electricity Consumption in the United Kingdom 258
9.3 The Logistic Model 259
9.4 The Combined Model 260
9.5 The ARIMA Models 263
9.5.1 Domestic ARIMA Model 263
9.5.2 Non-Domestic ARIMA Model 267
9.5.3 Total Electricity Consumption 270
9.6 Harvey Logistic and Harvey Models 272
9.7 The VAL Model 274
9.7.1 Estimation and Re-estimation of Saturation Levels 274
9.7.2 Developed VAL Models 278
9.7.3 Comparison with the Logistic Model 278
9.8 Comparison of the Models 279
9.8.1 Comparison of Model Fit and Forecasting Accuracy 279
9.8.2 Comparison of Forecasts 282
9.9 Summary 285

CHAPTER 10 WORLD ELECTRICITY CONSUMPTION FORECASTS 287

10.1 Introduction 287
10.2 World Electricity Consumption 288
10.3 Application of the Models 292
10.3.1 Logistic and Harvey Logistic Models 292
10.3.2 Combined Models 293
10.3.3 ARIMA Models 296
10.3.4 Application of the VAL Model 298
10.4 Forecasting Accuracy 303
10.4.1 Model Rankings 306

10.5 Comparison of Forecasts 309
10.5.1 North America 309
10.5.2 Central and South America 310
10.5.3 Western Europe 311
10.5.4 Industrialised Asia 313
10.5.5 Eastern Europe and the Former Soviet Union 314
10.5.6 Middle East 316
10.5.7 Africa 317
10.5.8 Developing Asia 318
10.5.9 World Total Electricity Consumption 320
10.6 Discussion 322
10.7 Summary 323

CHAPTER 11 OVERALL COMPARISON & FINDINGS 325

11.1 Introduction 325
11.2 Overall Performace at Country Level 325
11.3 Overall Performance at World Regional Level 327
11.4 Short, Medium and Long Term Forecasting 328
11.5 Overall Worst Models 329
11.6 Complexity of the Models 330
11.7 Findings 331
11.7.1 Simple Models Performed Better 331
11.7.2 Performance of the ARIMA Model 332
11.7.3 Best Model Fit does not necessarily mean the Best Model 332
11.7.4 Consistency of the Combined Model Forecasts 333
11.8 Differences in the Economies 333
11.9 Summary 335

CHAPTER 12 CONCLUSIONS AND FUTURE WORK 337

12.1 Conclusions of the Thesis 337
12.2 Future Work 341
12.2.1 Growth Curve Models 341

12.2.2 Regression and ARIMA Models 342
12.2.3 Neural Network Models 343
12.2.4 Further Testing of VAL Model 343

REFERENCES 345

APPENDIX A DATA FOR MALDIVES, NEW ZEALAND, UNITED STATES AND UNITED KINGDOM 371

A1. Male', Maldives 371
A2. New Zealand 372
A3. United States of America 373
A4. United Kingdom 374

APPENDIX B DATA FOR REGIONS AND WORLD TOTAL 375

B1. Electricity Consumption 375
B2. Gross Domestic Product (GDP) 376
B3. Population 377

LIST OF FIGURES

2.1 A typical intensity curve showing the stages of development 14
2.2 Electricity per capita for the 12 countries 17
2.3 GDP per capita for the 12 countries 17
2.4 Electricity intensity in the selected countries 18
2.5 Lower section of 2.4 enlarged 18
2.6 Electricity intensity curves for the selected countries 19
2.7 Electricity intensity curves for the industrialised countries 20
2.8 Electricity intensity curves for the developing countries 21
2.9 Electricity intensity factors for the industrialised countries 21
2.10 Electricity intensity factors for the developing countries 22
2.11 Electricity per capita for the regions of the world and world total 32
2.12 GDP per capita for the regions of the world and world total 32
2.13 Electricity intensity for the various regions of the world 33
2.14 Electricity intensity for the regions (2.13 enlarged) 33
2.15 Electricity intensity curves for the regions 34
2.16 Electricity intensity curves for the industrialised regions of the world 34
2.17 Electricity intensity curves for the developing regions of the world and world total 35
2.18 Electricity intensity factors for the various regions 36
2.19 Electricity intensity factors of 2.18 enlarged to show the lower section 37

4.1 Minimising SSR in the Fibonacci search technique 71

6.1 Electricity consumption in New Zealand 123
6.2 Fitted Logistic model for the Domestic sector of New Zealand 125
6.3 Fitted Logistic model for the Non-Domestic sector of New Zealand 126
6.4 Fitted Logistic model for the Total electricity consumption of New Zealand.... 126

6.5 Comparison of Logistic model with ESFC forecasts for Domestic sector 128

6.6 Comparison of Logistic model with ESFC forecasts for Non-Domestic sector . 128

6.7 Comparison of the Logistic model with ESFC forecasts for the Total consumption 129

6.8 Percentage variation of the electricity consumption compared with ESFC and Logistic models 129

6.9 Effect of historical data on the asymptotes for the Domestic sector 131

6.10 Effect of historical data on the asymptotes for the Non-Domestic sector 132

6.11 Effect of historical data on the asymptotes for the Total electricity consumption 132

6.12 GDP for New Zealand in current values from 1963-1999 136

6.13 Current GDP for New Zealand (1980-1999) with the best fitted straight line.... 137

6.14 Electricity consumption against current GDP (1980-1999) 138

6.15 Fitted Current GDP models for electricity consumption in New Zealand 140

6.16 Real GDP at 1991/92 prices for New Zealand from 1963 to 1999 141

6.17 Total electricity consumption of New Zealand from 1963 to 1999 142

6.18 Real GDP with the best fit straight line 143

6.19 Electricity consumption against real GDP (1963-99) with the fitted straight lines 144

6.20 Fitted Real GDP model (1963-1999) for electricity consumption in New Zealand 146

6.21 Fitted Real GDP models (1980-1999) for electricity consumption in New Zealand 147

6.22 Current electricity prices in New Zealand from 1960 to 1999 149

6.23 Current price from 1980 to 1999 along with the best fit straight line 149

6.24 Electricity consumption against current electricity price with the best fit lines . 150

6.25 Fitted Current Price models for electricity consumption in New Zealand 152

6.26 Fitted Combined models for electricity consumption in New Zealand 157

6.27 Plots of residuals against fitted values, GDP, price and population for total consumption 158

6.28 ACF and PACF of the original Domestic electricity consumption data 160

6.29 ACF and PACF of the first difference of the Domestic data 161

6.30 Fitted ARIMA(0,1,0) model for the Domestic electricity consumption 163

6.31 ACF and PACF of the residuals produced by ARIMA(0,1,0) for the Domestic sector ... 164
6.32 ACF and PACF plots of the original Non-Domestic consumption ... 164
6.33 ACF and PACF plots of the first differenced Non-Domestic data ... 165
6.34 ACF and PACF plots of the two times differenced Non-Domestic data ... 165
6.35 ARIMA(0,2,1) model fit for the Non-Domestic sector ... 167
6.36 ACF and PACF of the residuals produced by the fitted ARIMA(0,2,1) model for the Non-Domestic sector ... 168
6.37 ACF and PACF of the original Total electricity consumption data ... 169
6.38 ACF and PACF of first differenced Total consumption data ... 170
6.39 ARIMA(1,1,0) model fit for the Total electricity consumption ... 171
6.40 ACF and PACF of the residuals produced by the ARIMA(1,1,0) model for the Total electricity consumption ... 172
6.41 Plot of the regression line for the Domestic sector ... 173
6.42 Fitted Harvey Logistic models for electricity consumption in New Zealand ... 174
6.43 Fitted Harvey models for New Zealand electricity consumption ... 175
6.44 Saturation levels using Fibonacci search technique ... 177
6.45 Forecasting accuracies of the four models for Domestic sector ... 181
6.46 Forecasting accuracies of the four models for the Total electricity consumption 181
6.47 Saturation estimation by the VAL models ... 183
6.48 Comparison of forecasts by VAL model and Logistic model ... 184
6.49 Forecasting accuracies of the VAL and Logistic models ... 185
6.50 Forecasting accuracies of the six developed models for New Zealand ... 186
6.51 Comparison of forecasts for the Domestic sector of New Zealand ... 190
6.52 Comparison of forecasts for the Non-Domestic sector of New Zealand ... 191
6.53 Comparison of Total electricity consumption forecasts for New Zealand ... 191

7.1 Annual electricity consumption in Male', Maldives ... 195
7.2 Fitted Logistic models for electricity consumption in Male' (Maldives) ... 197
7.3 Fitted Combined models for electricity consumption in Male' (Maldives) ... 199
7.4 Residuals against the fitted values and variables for Male' ... 200
7.5 Fitted Harvey Logistic models for Male' (Maldives) ... 201
7.6 Fitted Harvey models for Male' (Maldives) ... 201

7.7 ACF and PACF of original Domestic consumption data 203
7.8 ACF and PACF of differenced data for the Domestic sector 203
7.9 Fitted ARIMA(1,1,2) model for the Domestic sector (MAPE = 9.9) 204
7.10 ACF and PACF of the residuals for the Domestic sector 205
7.11 ACF and PACF of the original Non-Domestic consumption 206
7.12 ACF and PACF of first differenced Non-Domestic data 207
7.13 ACF and PACF of twice differenced data (Non-Domestic sector) 207
7.14 Fitted ARIMA(0,2,1) model estimates for the Non-Domestic sector (MAPE = 7.3) 208
7.15 ACF and PACF of the ARIMA(0,2,1) model for Non-Domestic sector 209
7.16 ACF and PACF of the original Total consumption data 210
7.17 ACF and PACF of the first differenced Total consumption data 210
7.18 ACF and PACF of twice differenced Total consumption data 211
7.19 Fitted ARIMA (2,2,0) for the Total electricity consumption (MAPE = 5.4) 212
7.20 ACF and PACF of the residuals produced by the ARIMA(2,2,0) for Total consumption 212
7.21 Estimated saturation levels of the Domestic sector 214
7.22 Estimated saturation levels of the Non-Domestic sector 214
7.23 Estimated saturation levels for the Total consumption 215
7.24 Forecasts of the VAL and Logistic models along with the actual data 215
7.25 Forecasting accuracies of the developed models for Male' 217
7.26 Comparison of Domestic forecasts for the Maldives 219
7.27 Comparison of Non-Domestic forecasts for the Maldives 220
7.28 Comparison of Total electricity consumption forecasts for the Maldives 220

8.1 Annual electricity consumption in the United States 1949-2002 226
8.2 Fitted Logistic models for the United States 227
8.3 Residuals against the fitted variables of the Combined model 230
8.4 Fitted Combined models for the United States 230
8.5 ACF and PACF plots of the Domestic sector for the United States 232
8.6 ACF and PACF plots of the differenced Domestic data 232
8.7 Fitted ARIMA(3,1,3) model for the Domestic sector (MAPE = 2.28) 233
8.8 ACF and PACF of the residuals produced for the Domestic sector 234

8.9 ACF and PACF plots of the differenced Non-Domestic data 235
8.10 Fitted ARIMA(0,1,0) for the Non-Domestic sector (MAPE = 2.51) 236
8.11 ACF and PACF of the residuals produced for the Non-Domestic sector 237
8.12 ACF and PACF of the differenced Total consumption data 238
8.13 ARIMA(0,1,0) estimate of the Total electricity consumption (MAPE = 2.56) .. 239
8.14 ACF and PACF of the residuals for the Total electricity consumption 239
8.15 Fitted Harvey Logistic models for the United States 241
8.16 Fitted Harvey models for the United States 241
8.17 Saturation levels obtained by the Fibonacci search technique from 1984-2002 242
8.18 Forecasting accuracy of the various VAL models for the United States 245
8.19 Saturation level estimated by the VAL models 247
8.20 Comparison of forecasting accuracies of the VAL model and Logistic model .. 248
8.21 Forecasting accuracies of all models for the United States 249
8.22 Comparison of Domestic forecasts by all the developed models for the USA ... 251
8.23 Comparison of Non-Domestic forecasts by all the developed models for the USA 252
8.24 Comparison of Total consumption forecasts by all the developed models for USA 252

9.1 Electricity consumption in the United Kingdom from 1965 to 2002 258
9.2 Fitted Logistic models for electricity consumption in the UK 259
9.3 Residuals against the fitted variables of the Combined model 262
9.4 Fitted Combined models for electricity consumption in the UK 263
9.5 ACF and PACF of the original Domestic data for the UK 264
9.6 ACF and PACF of differenced Domestic data 265
9.7 Fitted ARIMA model for the Domestic sector of the UK (MAPE = 2.17) 266
9.8 ACF and PACF of the residuals for the Domestic sector 266
9.9 ACF and PACF plots of original Non-Domestic data for the UK 267
9.10 ACF and PACF of the differenced Non-Domestic data 268
9.11 Fitted ARIMA model for the Non-Domestic sector of the UK (MAPE = 2.25) 269
9.12 ACF and PACF of the residuals for the Non-Domestic model 269
9.13 Fitted ARIMA model for the Total electricity consumption (MAPE = 1.82) 271

9.14 ACF and PACF of the residuals given by the Total consumption model for the UK 271
9.15 Fitted Harvey Logistic models for the UK 273
9.16 Fitted Harvey models for the UK 273
9.17 Saturation levels obtained by Fibonacci search technique for the UK 274
9.18 Estimated Domestic saturation levels by the VAL model 276
9.19 Estimated Non-Domestic saturation levels by the VAL model 276
9.20 Estimated Total consumption saturation levels by the VAL model 277
9.21 Forecasting accuracy of the Logistic model with VAL model 279
9.22 Forecasting accuracies of all models for the UK 280
9.23 Comparison of the Domestic forecasts by all the developed models for the UK283
9.24 Comparison of the Non-Domestic forecasts by all the developed models for the UK 283
9.25 Comparison of the Total consumption forecasts by all the models for the UK..284

10.1 Electricity consumption in the world (8 regions) 291
10.2 World total electricity consumption from 1980 to 2002 291
10.3 Fitted Logistic, Harvey Logistic and Harvey models for the world total electricity consumption 294
10.4 Combined model fit for the world total electricity consumption 296
10.5 ACF and PACF of the residuals produced by the ARIMA model for the world total 298
10.6 Fitted ARIMA model for the world total electricity consumption 299
10.7 Saturation levels for all regions and world total 299
10.8 10.7 enlarged to show the unclear regions 300
10.9 World electricity consumption estimated by the VAL model and the Logistic model 302
10.10 Accuracy plots for North America, Central & South America and Western Europe 304
10.11 Accuracy plots for Industrialised Asia, Eastern Europe & the FSU and Middle East 305
10.12 Accuracy plots for Africa, Developing Asia and world total electricity consumption 305

10.13 Comparison of forecasts for North America.. 309
10.14 Comparison of forecasts for Central and South America 311
10.15 Comparison of forecasts for Western Europe.. 312
10.16 Comparison of forecasts for Industrialised Asia... 313
10.17 Comparison of forecasts for Eastern Europe and the Former Soviet Union..... 315
10.18 Comparison of forecasts for the Middle East 316
10.19 Comparison of forecast for Africa 318
10.20 Comparison of forecasts for Developing Asia... 319
10.21 Comparison of forecasts for world total electricity consumption..................... 320

LIST OF TABLES

2.1 Percentage electricity generation by type at 2001 23

4.1 First 21 Fibonacci Numbers 69

6.1 Autocorrelation coefficients for New Zealand 124
6.2 Logistic model asymptotes and the corresponding SSR values for New Zealand 124
6.3 Sets of asymptotic levels for Domestic, Non-Domestic and Total consumption 131
6.4 Coefficients of the electricity consumption versus current GDP 137
6.5 Statistical results of electricity consumption versus current GDP (1980-1999). 138
6.6 Constant terms of the Current GDP models 141
6.7 Coefficients of the fitted straight lines for real GDP versus electricity consumption (1963-99) 144
6.8 Statistical results for real GDP and electricity consumption (1963 – 1999) 145
6.9 Constants of the Real GDP model (1963-1999) 145
6.10 Statistical test results for the Real GDP model (1980-1999) 146
6.11 Coefficients of the Real GDP model (1980-1999) 147
6.12 Coefficients of the best fitted lines for price versus electricity consumption 151
6.13 Statistical test results for electricity price versus consumption 151
6.14 Coefficients of the Current Price models 152
6.15 Correlation matrix for variables used in the Combined model 155
6.16 Validity test results for the Combined models 156
6.17 Comparison of model fits for the econometric models proposed for New Zealand 159
6.18 ARIMA models and the corresponding AICC values for Domestic sector 162

6.19 ARIMA models and the corresponding AICC values for the Non-Domestic sector 166
6.20 ARIMA models and the corresponding AICC values for the Total consumption 170
6.21 Correlation between the saturation levels and the explaining variables 178
6.22 Statistical test results of the various models for the data set from 1984-1999.... 179
6.23 Rankings of the models for New Zealand (1 = best, 6 = worst) 187

7.1 Asymptotic values for Male' by Fibonacci search technique 196
7.2 Correlation matrix for the variables of Male' 197
7.3 Validity test results for Male' 198
7.4 Rankings of models in terms of model fit and forecasting accuracy (1 = best model, 5 = worst model) 217

8.1 Saturation levels for the USA by Fibonacci search technique 226
8.2 Correlation coefficients between the selected variables and the electricity consumption 228
8.3 Validity test results for the USA 229
8.4 Correlation between the explaining variables and the saturation levels 243
8.5 Statistical test results for re-estimation of saturation levels 244
8.6 Rankings of the models developed for the USA (1 = best model, 6 = worst model) 249
8.7 Comparison of EIA projections with the developed models for Total electricity consumption 253

9.1 Correlation coefficients between the variables and electricity consumption in the UK 260
9.2 Statistical validity test results for the UK 261
9.3 MAPE value for the fitted Harvey Logistic and Harvey models for the UK...... 272
9.4 Correlation between the explaining variables and saturation levels 275
9.5 Statistical test results for re-estimation of saturation levels 277
9.6 Model rankings for the United Kingdom (1 = best, 6 = worst).......................... 281

9.7 Comparison of EIA projections with the developed models for Total electricity consumption of the United Kingdom (% Difference to the EIA projections) .. 285

10.1 MAPE and DW values for world electricity consumption ... 293
10.2 Statistical tests and fitting of the Combined models for the world data ... 295
10.3 Statistical test results and model fits for the ARIMA models ... 297
10.4 Statistical test results for estimation of saturation levels and electricity consumption by the VAL model ... 301
10.5 Rankings of models for all regions (1 = best model and 5 = worst model) ... 307
10.6 Comparison of forecasts with EIA projections for North America ... 310
10.7 Comparison of forecasts with EIA projections for Central and South America. 311
10.8 Comparison of EIA forecasts with the developed model forecasts for Western Europe ... 312
10.9 Comparison of the EIA forecasts with the developed models for Industrialised Asia ... 314
10.10 Comparison of EIA projections with the developed models for Eastern Europe and the FSU ... 315
10.11 Comparison of EIA forecasts with the developed models for Middle East ... 317
10.12 Comparison of the EIA forecasts with the developed models for Africa ... 318
10.13 Comparison of EIA forecasts with the developed models for Developing Asia ... 320
10.14 Comparison of EIA forecasts with the developed models for world total electricity consumption ... 321

11.1 Overall best and second best models for New Zealand, the Maldives, the United States and the United Kingdom ... 326
11.2 Individual model rankings for world electricity consumption ... 327
11.3 Best models for short, medium and long terms forecasts ... 328
11.4 Number of times each of the models is ranked worst and second worst ... 329

Chapter 1

INTRODUCTION

1.1 GENERAL

Electricity is one of the most dominant forms of energy. The ideal choice for the carrier of energy in advanced economies is electricity. The flexibility of electricity as an energy carrier has contributed to technological innovation and increased industrial productivity. Some of the most common advantages of electricity as a future carrier of energy include its cleanliness, versatility, accessibility and simplicity in distribution [Khatib, 1993]. These advantages have contributed to the increased share of electricity in the total energy consumption in many countries [Nilsson, 1993].

The increased use of electricity from residential homes to industry has contributed to the increasing demand in electricity consumption worldwide. The growth in demand is even higher in developing countries as the robust economic growth boosts demand for new electrical appliances [EIA_1, 2004]. Although the rate of growth in electricity consumption may be slower in the industrialised countries, their dependence on electricity may even be higher than the developing countries.

The high demand due to the heavy dependence on electricity requires planning of resources of electricity well in advance to ensure a continuous supply of electricity in the future. This requires careful measurement and observation of the patterns of electricity use and its prediction into the future. This is the role of forecasting. Hence, forecasting electricity is one of the most important aspects of electric utility planning.

Electricity forecasting forms the basis of power system expansion planning, and affects system security and reliability [Kandil *et al.*, 2001] [Abdel-Aal and Al-Garni, 1997] [Darbellay and Slama, 2000]. Forecasting electricity can be generally classified into three categories based on discrete forecast range. Firstly, short term forecasting of a few hours ahead to a few days ahead plays an important role in the day-to-day operation and scheduling of generating units [Methaprayoon, 2003] [Al-Alawi and Islam, 1996]. Secondly, medium term forecasting over a period of a few weeks to a few months, and in some cases to a few years, is mainly useful for fuel allocation and maintenance scheduling [Methaprayoon, 2003] [Al-Alawi and Islam, 1996]. Finally, long term forecasts over a period of 5 to 25 years [Al-Alawi and Islam, 1996] are needed to determine appropriate size and type of new generation units to be constructed to assure adequate generation capacity [Methaprayoon, 2003]. Therefore, long term forecasts of national electricity consumption assist the government and private sectors in the long term planning of the electricity industry, such as when and where to build a power plant or when to expand capacity.

1.2 THESIS OBJECTIVES

A number of electricity load forecasting models have been proposed in the past, including short and long term load forecasting using neural nets [Kermanshashi and Iwamiya, 2002] [Huang *et al.*, 2002] [Chen *et al.*, 2001] [Becalli *et al.*, 2004] [Hsu and Chen, 2003], fuzzy methods [Al-Kandari and Soliman, 2004] [Vellasco *et al.*, 2004] [Ranaweera *et al.*, 1996] [Mori and Kobayashi, 1996] and combinations of neural nets and fuzzy methods [Liang and Cheng, 2002] [Padmakumari and Mohandas, 1999] [Iyer *et al.*, 2003] [Abraham and Nath, 2001]. Forecasting electricity consumption has been applied using many theoretical methods including growth curves [Mohamed and Bodger, 2003] [Bodger and Tay, 1987] [Skiadas *et al.*, 1993] [Sharp and Price, 1990] [Young, 1993] [Tingyan, 1990], multiple linear regression methods that use economic, social, geographic and demographic factors [Egelioglu *et al.*, 2001] [Harris and Liu, 1993]

[Yan, 1998] [Rajan and Jain, 1999] [Fung and Tummala, 1993] [Liu *et al.*, 1991], and Box-Jenkins autoregressive integrated moving average (ARIMA) techniques [Abdel-Aal and Al-Garni, 1997] [Chavez *et al.*, 1999] [Saab *et al.*, 2001] [Wong and Rad, 1998] [Gross and Galiana, 1987] [Hagan and Behr, 1987].

The main objective of this thesis is to present the applicability of simple forecasting models in long term electricity forecasting as compared to the more complex and conventional techniques that have been used in the past. The thesis concentrates on testing and comparing the performances of the various models when applied to different data sets. Although the period considered for long term forecasting is different from country to country and even from company to company [Kermanshahi and Iwamiya, 2002], such forecasting models have been generally analysed around over a period ranging from 10 to 15 years ahead [Fung and Tummala, 1993] [[Kandil *et al.*, 2001] [Methaprayoon, 2003] [Al-Alawi and Islam, 1996] [Kermanshahi and Iwamiya, 2002]. Hence, the main focus is on long term electricity forecasting of around 15 years ahead. However, the performances of the models in the short and medium term ranging from 1 to 5 years are also analysed.

This research aims to add to the current literature on electricity forecasting by proposing and comparing various electricity forecasting models for selected countries, various regions of the world and world total electricity consumption. The proposed models are three growth curve models (*Logistic* model, *Harvey Logistic* model and *Harvey* model), a multiple linear regression model using economic and demographic variables (*Combined* model), an autoregressive integrated moving average (*ARIMA*) model, and a Variable Asymptote Logistic (*VAL*) model that combines the economic variables into the Logistic model and employs the ARIMA technique to forecast the variables. The developed models are compared against each other using their ability to fit historical electricity consumption and the accuracy of the forecasts.

Although, the artificial neural networks (ANNs) and fuzzy logic models have performed well with particular data sets in short term load forecasting, they have been criticised due to the intuitive relation to the process which determines demand and have not gained the confidence of the electricity supply industries [Infield and Zunko, 1998]. In addition, a key limitation of the ANNs is their relative inability to adapt to reflect changing conditions [Ranweera *et al.*, 1996]. This research does not attempt to propose the most accurate model by making a model complex, but aims to demonstrate the performance of the proposed simple growth curve models to forecast electricity consumption as compared to the more complex econometric or ARIMA modelling techniques that have been frequently applied in forecasting. As compared to the growth curve models, in econometric modelling the independent variables such as gross domestic product (GDP), population and price of electricity need to be independently forecasted before any forecasts can be made. In addition, the ARIMA technique has been regarded by many forecasters as a very complex technique due to the mathematical complexity, time and experience required to apply the technique to a particular data set. While the proposed regression and ARIMA models and the process of application of these models to the different data sets provide significant contributions to the current literature on electricity forecasting, they will also serve as benchmarks to compare the performances of the simple growth curve models that in recent years have not often been applied in electricity forecasting. Apart from the application of the Logistic model to electricity forecasting [Bodger and Tay, 1987], the Harvey Logistic and the Harvey models have not been applied to electricity consumption forecasting previously. In addition, the VAL model is also a new model proposed for forecasting electricity consumption, although it may show some similarity to the modified logistic model [Skiadas *et al.*, 1993].

Electricity consumption has been often related to GDP and population in many previous studies [Huang, 1993] [Sun, 2002] [Alcantara and Duro, 2004] [Unander *et al.*, 2004] [Corrillie and Fankhauser, 2004] [Nilsson, 1993] [Meyers and Sathaye, 1989] [Sun, 2003] [Sun and Kuntsi, 2004] [Alcantara and Duarte, 2004]. Therefore, this research initially investigates the relationship between electricity consumption and economic growth for twelve countries that include six industrialised countries and six developing countries. In addition to the four countries to which the forecasting models are applied (New Zealand, the Maldives, the United States and the United Kingdom), the rest of the countries are selected on the basis of having the world's highest electricity consumptions, the world's largest economies, and/or the world's largest populations. The relationship between the aggregate electricity consumption and economic growth for these countries is analysed using the various methods for a period of 23 years in an attempt to endorse why GDP and population are used in the Combined and VAL models while forecasting electricity consumption. As this research proposes a set of growth curves and ARIMA models that do not require any variables as such, the use of these factors in the Combined and VAL models provides an explanation as to whether the use of these variables gives rise to any better models.

Some researchers have demonstrated the need to analyse the sensitivity of the electricity forecasts due to the changes in input variables [Abu-El-Magd *et al.*, 2003] [Sailer, 2001] [Kermanshahi, 1998] [Jia *et al.*, 2001] [Elkateb *et al.*, 1998]. Only two of the six proposed electricity forecasting models in this thesis use external variables. Therefore, a sensitivity analysis for the other four models cannot be performed as they all rely purely on the historical electricity consumption data. Sensitivity analyses of these two models would not be very helpful when comparing all six models and therefore have not been included in this research.

The accuracy of electricity forecasting models has varied from model to model over the various periods they have been applied. In general, it is easier to get more accurate short term forecasts as compared to long term forecasts [Ku, 2002]. Short term forecasts generally rely on more precise information on the variables used in such a forecasting model. However, it has been reported that a 2% error has been noted within any half-hour period when forecasting load in Great Britain [Ku, 2002]. Hyde and Hodnett [Hyde and Hodnett, 1997] concluded that a 2% error is within the required bounds for good performance in short term electricity forecasting. In medium term load forecasting, an ARIMA model has achieved 11.7% error, while the best artificial neural network (ANN) and fuzzy neural network (FNN) models have achieved errors of 6.8% and 4.7% respectively [Elkateb *et al.*, 1998]. Yalcinoz and Eminoglu [Yalcinoz and Eminoglu, 2005] concluded that a 6.84% error in medium term forecasting is very good. A long term forecasting approach based on new dynamic simulation theory gave a mean error within 3% for a five year period [Jia *et al.*, 2001]. On the other hand, it was reported that a 10% error in forecasting is generally acceptable for long term forecasting of Japanese power companies [Kermanshahi and Iwamiya, 2002]. Hence, there is no prescribed limit for a forecast to be useful. Forecasting accuracy is generally used to compare the performances of a model relative to other models. In this research, attempts are made to propose models with the lowest possible forecasting errors.

Many electricity industries today have undergone or are in the process of undergoing structural change from the previous traditionally highly regulated industry to a competitive industry. Deregulation and restructuring of the electricity supply industry is one of the most important global energy developments of the last century [Hamalainen *et al.*, 2000]. Traditionally, the electric power industry was based on the theory that the electric power production, transmission and distribution were natural monopolies. It was also believed that large centralised power plants were the most efficient and inexpensive means of producing electric power. Therefore, the research also investigates whether deregulation has had any significant effect on the patterns of electricity consumption for the selected countries.

The thesis then applies the forecasting models to New Zealand electricity consumption, the country where the research has been conducted. The research began as a revisit to study the applicability of the Logistic model in long term electricity forecasting that has been studied previously in this department [Tay, 1985]. Due to some constraints in forecasts by the Logistic model, the research was extended to study the other growth curve models that have been proposed. However, the performances of these simple growth curve models can only be evaluated by comparing them with some of the most commonly used techniques such as ARIMA and econometric methods. This has led to the various different models that have been proposed and compared in this thesis. Very detailed analyses in applying the models to electricity forecasting in New Zealand are discussed. The success of the proposed models in forecasting electricity in New Zealand has led to the application and analysis of the same models to the very small developing country the Maldives where the author comes from. The models have further been applied to the United States of America and the United Kingdom. The forecasts given by the models are compared with national or other electricity forecasts where available.

The forecasting of electricity is extended from the country level to regional levels of the world and the world total electricity consumption. The world electricity consumption is divided into eight regions that include three industrialised regions and five developing regions. The industrialised regions are North America, Western Europe and Industrialised Asia. The developing regions are Central and South America, Eastern Europe and Former Soviet Union, Middle East, Africa and Developing Asia.

1.3 THESIS OUTLINE

Chapter 2 initially investigates the patterns of electricity consumption in relation to GDP and population for selected countries and regions of the world. The chapter then investigates whether deregulation of the electricity industry has affected these patterns.

Chapter 3 describes the theory of the statistical tests that are used in analysing and comparing the electricity forecasting models with one another.

Chapter 4 describes in theoretical detail the six proposed electricity forecasting models. The models are presented along with a review of the applications of the respective models in forecasting.

Chapter 5 gives a historical overview of the developments of the New Zealand electricity industry which has formed the basis of this research. By studying the historical developments of the electricity industry in New Zealand, an overall idea of the complexity of electricity developments in other countries can be appreciated.

Chapter 6 applies the developed forecasting models to the electricity consumption data of New Zealand. The models are tested using the relevant statistical tests described in Chapter 3. The models are compared against each other on their ability to fit the historical data as well as on how accurate they forecast electricity consumption. The forecasts from these models are compared with available national forecasts.

Chapter 7 applies the developed models to the electricity consumption data in the Maldives. A brief history of electricity development in the Maldives is also presented. The applied models for the Maldives are also compared for the goodness of fit and forecasting accuracy. The forecasts by the developed models are also presented.

Chapter 8 applies the developed models to the electricity consumption data in the United States of America. The chapter begins with a brief overview of electricity developments in the United States. The developed models are compared using model fit and forecasting accuracy. The forecasts by the developed models are also compared with the national forecasts of the United States.

Chapter 9 applies the developed models to the electricity consumption in the United Kingdom. After a brief overview of the electricity industry in the United Kingdom, the models are applied and compared as for the other three countries. The chapter is concluded after presenting a set of forecasts from the applied models and comparing with some other forecasts.

Chapter 10 applies the developed models to world electricity consumption data. The world data along with the data from eight regions of the world are separately used in applying the models and to compare the forecasts. Forecasts for each of these regions and world total are presented and compared with the Energy Information Administration (EIA) [EIA_1, 2004] forecasts.

Chapter 11 gives an overall comparison of the developed models across the country and regional levels. This chapter also summarises the major findings of the thesis.

Chapter 12 summarises the main conclusions of the research and recommends directions for future research and development in electricity forecasting.

Chapter 2

ELECTRICITY PATTERNS AND DEREGULATION

2.1 INTRODUCTION

It has been strongly believed that future growth in an economy is not possible without growth in electricity. As a result, the relationship between economic wealth and electricity consumption has been studied in a number of studies [Huang, 1993] [Sun, 2002] [Alcantara and Duro, 2004] [Unander *et al.*, 2004] [Cornillie and Fankhauser, 2004] [Nilsson, 1993] [Meyers and Sathaye, 1989] [Sun, 2003] [Sun and Kunsi, 2004] [Alcantara and Duarte, 2004] and in particular on understanding the correlation between economic growth and energy consumption. In the meantime, the proportion of electricity in the total energy consumption worldwide has increased rapidly.

Electricity intensity which measures the relationship between electricity consumption and gross domestic product (GDP) is an important factor in understanding the changes in electricity consumption over time. A number of underlying factors are reflected by changes in the ratio, such as the state of technology, the price of electricity, the composition of GDP, the levels of activity in individual electricity using sectors, and demographic and sociological factors [Huang, 1993]. Electricity intensity may also reflect economic structure, fuel mix and the level of technology in a country, as these factors are reflected by the corresponding energy intensity [Sun, 2002].

In international comparisons, it seems fairly reasonable to perceive energy intensity as a synthetic indicator of efficient energy use [Alcantara and Duro, 2004]. Although energy intensities are related to the inverse of energy efficiency, they are not equivalent. For example, an increase in energy efficiency can help to reduce the energy intensities while changes in other factors such as usage patterns can either augment or counter-balance the impact of improved efficiencies on energy intensity [Unander *et al.*, 2004]. However, the difference in energy intensity should not be confused with the difference in energy efficiency as energy use depends on socio-economic and environmental circumstances such as comparative advantages for energy intensive activity, resource endowment, population density and climate, while energy efficiency indicates a measure of how resourcefully energy is used under these conditions and given prices [Cornillie and Fankhauser, 2004]. Therefore, a comparison of energy intensity picks up differences in both the efficiency and socio-economic conditions.

Higher end-use and conversion efficiencies can help to reduce primary energy use and improve energy efficiency while maintaining a given level of energy services [Nilsson, 1993]. Advances in technology have improved the efficiency by which the energy services are provided. The ideal choice for the carrier of energy in advanced economies appears to be electricity [Nilsson, 1993]. Therefore, the proportion of electricity in the total energy consumed has increased significantly. The efficiencies of electricity generation, distribution and equipment used in residential homes and industrial machines have improved significantly. Therefore, the increased use of electricity has been noted as an important contributing factor to the reduction of the overall energy intensities in many countries [Nilsson, 1993].

In many countries, electricity consumption has grown much faster than economic growth due to the mechanisation of industrial and agricultural production and increased use of electricity in residences and other buildings [Meyers and Sathaye, 1989]. The growth rate of electricity consumption depends to some degree on the stage of economic development of a country. For example, it has been shown that electricity intensities in the wealthier Asian developing countries are lower than the other developing countries [Meyers and Sathaye, 1989]. This reflects that the wealthier countries have achieved a more mature phase of economic development. In general, increased industrialisation, urbanisation, a greater demand for the development of transport, infrastructure and the modernisation of life styles in the developing countries have resulted in high energy intensity trends [Sun, 2003] [Sun and Kuntsi, 2004].

From an ecological perspective, lowering energy intensity has been considered beneficial. This has been the basis of numerous researches on the evolution of energy intensities [Alcantara and Duarte, 2004]. This usually involves breaking down the consumption into explicative factors. Schfer [Schfer, 2005] indicated that the decline in energy intensities is caused by two underlying factors. They are the improvements in energy efficiency and economic structural change. In order to study the impact of structural change a number of decomposition analysis techniques have been developed. Ang and Zhang [Ang and Zhang, 2000] surveyed more than one hundred of these studies based on application area, aggregate indicator and decomposition scheme to study the impact of changes in product mix on industrial energy demand. Although, no major conclusions are presented, the survey presents a review of the index decomposition techniques that have been applied previously.

In this chapter, the relationship between the patterns of electricity consumption, and GDP and population are studied over the period 1980-2002. The electricity intensity and its various transformations using population for 12 selected countries and regions are presented and analysed. The first four countries selected are the countries to which the forecasting models will be later applied. They are New Zealand, the United States, the United Kingdom and the Maldives. The other eight countries are selected using three different criteria. Firstly, the five countries that consumed the highest amount of electricity in 2002 are selected [EIA_2, 2004]. They are the United States (3660 TWh), China (1457 TWh), Japan (971 TWh), Russia (780 TWh) and Germany (513 TWh). India and Canada were ranked very close sixth and seventh with consumptions of 511 TWh and 487 TWh respectively [EIA_2, 2004]. Secondly, the five countries that accounted for the highest GDP values at 2002 are selected. They are the United States, Japan, Germany, France and the United Kingdom in that order [EIA_2, 2004]. Finally, the five countries with the largest populations at 2002 are selected. They are China, India, the United States, Indonesia and Brazil in order of decreasing population [EIA_2, 2004]. The inclusion of the United States in all the three categories, and inclusion of

China, Japan and Germany in two categories, takes the total number of countries selected in this study to 12. They are New Zealand, the United States, the United Kingdom, the Maldives, China, Japan, Russia, Germany, France, India, Indonesia and Brazil. All the data used in this chapter are obtained from the Energy Information Administration [EIA_2, 2004].

In addition, the analysis extends to the different regions of the world, and to the world total electricity consumption to which the forecasting models will also be applied. The regions are North America (industrialised), Central and South America, Western Europe (industrialised), Eastern Europe and the Former Soviet Union (FSU), Industrialised Asia, Middle East, Africa and developing Asia. Details of the various countries in each of these groups are given in Chapter 10.

GDP and population will be used in all of the Combined and VAL models to be proposed. This analysis will reinforce why these variables are selected when one could use a lot more than two variables in the multiple linear regression models. If the analysis supports the available literature that electricity consumption and GDP are related, then the choice of these variables in these models can be justified. Therefore, it can be argued that the use of these variables in a forecasting model should produce better forecasts than those models that do not use any other variables. This question will be answered towards the end of the thesis when the forecasting models are compared. In addition, the patterns of electricity consumption and electricity intensity, and the various factors that may influence these changes will also be discussed, as studying these could enhance the understanding of the electricity industry and factors that may influence the industry.

The last two decades, and especially the last decade, has been a period of deregulation of many electric power industries whereby traditional economic regulation gave way to policies grounded in the faith that competitive markets will do a better job of protecting the interests of the public [Haar, 2004]. As the competitive complexity and intensity increase, the deregulated companies are faced with the challenge of learning without experience as they compete with new industries, with new rules and against unfamiliar competitors [Lomi and Larsen, 1999]. Any changes that significantly affect the pattern of electricity consumption may affect the performances of the models to be proposed as the models are based on time series extrapolation techniques. Therefore, this chapter analyses whether deregulation has had any effect on the electricity consumption patterns for the countries and regions, and briefly discusses the issues and implications of deregulation in general.

2. 2 DEFINITIONS

2.2.1 Electricity Intensity

Electricity Intensity (EI) is defined as the relationship between electricity consumption and GDP. This is expressed as

$$EI = \frac{Consumption}{GDP} \tag{2.1}$$

Electricity intensity is an important factor that reflects changes in electricity consumption over time in the production of an economy. Although it is believed that economic growth and electricity demand are linked, the strength of the relationship is different from region to region and depends on the stage of development of a country or region [EIA_1, 2004]. A number of reasons may exist for changes in electricity intensity within a particular sector of industry. They include the growth or decline of electricity-specific end-uses, like motive power and electrolysis (or changes in their efficiency), increases in the use of electricity at the expense of other fuels, or the development of new electricity technology [Hankinson and Rhys, 1983].

2.2.2 Electricity Intensity Curve

The electricity intensity curve (EIC) shows the stage of development of electrical energy in the process of GDP output [Bodger, 1984]. The EIC attempts to obtain the relationship between the electricity intensity and the level of wealth in a country as measured by GDP per capita. Therefore, the EIC is obtained by graphing the electricity intensity against GDP per capita. The slope of the curve may assist in determining whether the electrical industry is in a growth, mature or ageing phase [Bodger, 1984]. A typical intensity curve of an input to industry is shown in Figure 2.1 [Harvey and Gibbs, 1980]. The growth phase represents the rapid expansion of the input to industry either due to new industrial growth or substitution of other products [Bodger, 1984]. The mature phase shows a saturation of market penetration of the input to the industry. Finally, the ageing phase represents a decline in intensity. This implies a substitution of the input to industry by some new inputs. The maturing and ageing phases do not necessary imply a decline in absolute consumption [Bodger, 1984].

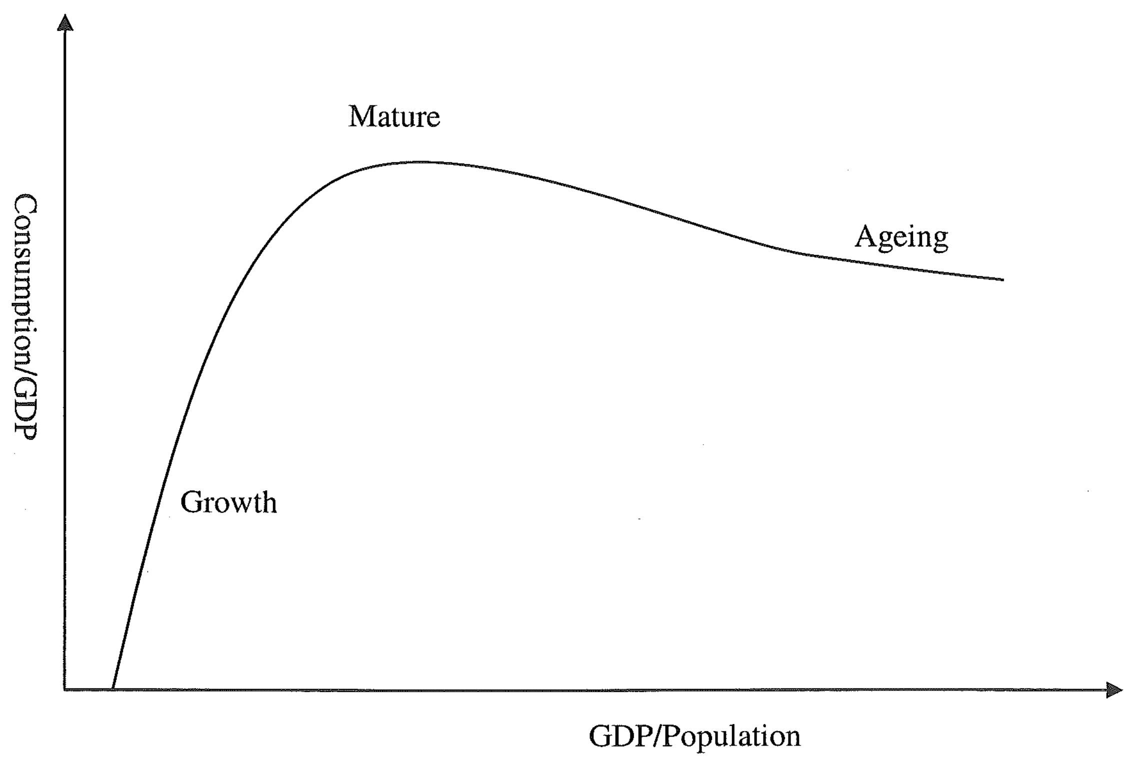

Figure 2.1 A typical intensity curve showing the stages of development

2.2.3 Electricity Intensity Factor

Each point on the intensity curve represents a combination of consumption, GDP and population for a particular year [Bodger, 1984]. This is called electricity intensity factor (EIF). These points can be graphed against time. The EIF is defined as [Bodger, 1984]

$$EIF = \frac{Consumption / GDP}{GDP / Population}$$

$$= \frac{Consumption \times Population}{GDP^2} \qquad (2.2)$$

Graphing the EIF in this way gives a historical evaluation of the variation of this factor with time.

2.3 INTENSITY IN SELECTED COUNTRIES

2.3.1 Results

In this section, the relationship between electricity consumption, GDP and population of the selected countries are analysed. Graphs of electricity consumption per capita, GDP per capita, electricity intensity, electricity intensity curves and electricity intensity factors are studied. Figure 2.2 shows the electricity per capita for the 12 countries. The electricity consumption per capita is highest in the United States while New Zealand is the second highest in electricity consumption per capita. The electricity consumption per capita in the other four industrialised countries, the United Kingdom, Japan, Germany and France, are very similar and are towards the centre of the plots. On the other hand, the electricity consumed in the developing countries except for Russia, are very low compared to the industrialised countries. The data for Russia prior to 1992 was not used due to inconsistencies observed while trying to incorporate the data of former USSR from 1980 to 1991.

Figure 2.3 shows the GDP per capita for the 12 countries. Japan shows the highest GDP per capita of the 12 countries presented. The GDP per capita for the United States, Germany and France are very similar and are the next highest. The United Kingdom and New Zealand, below these, have very similar GDP per capita throughout the period. As expected, the GDP per capita for the six developing countries are the lowest.

The comparisons show that in general the per capita electricity use is higher for countries with the higher incomes. Although the per capita electricity use increases as the low income economies develop, it can be seen here that there are large differences in the level of per capita electricity use between the developing countries and the industrialised countries. A similar observation between energy per capita and GDP per capita had been observed by Nilsson [Nilsson, 1993]. Meyers and Sathaye [Meyers and Sathaye, 1989] concluded that higher level of electricity use reflects the greater income per capita and the degree of urbanisation in these countries. This shows that there is a strong relationship between electricity per capita and GDP per capita.

Figure 2.4 shows the electricity intensity in these countries. The electricity intensity is highest in Russia. China has the second highest electricity intensity with a decreasing trend. The electricity intensity in India has increased over the years, peaked around 2000 and shows a decline in electricity intensity from 2000-2002. New Zealand has the fourth highest electricity intensity throughout the period. For the other countries, the difference in electricity intensity is small.

The smaller variations in the pattern of electricity intensity for these countries are shown in Figure 2.5. In the United States and the United Kingdom, the electricity intensity has decreased over the years, although the size of this decrease is small. In Brazil, the electricity intensity continued to increase except for the sudden decrease from 2000 to 2001. In France, the electricity intensity increased slightly initially, peaked around 1995 and continued to decrease slightly in the later years. Japan shows the smallest variations over the 23 years compared. The electricity intensity in Japan has continued around a constant value between 0.146 and 0.172 kWh/1995 US$. Indonesia shows the largest variations in electricity intensity over the whole period. The electricity intensity in Indonesia was at the same low level as for Japan and continued to increase to the level of intensity in the United Kingdom and then declined from 1990-1993. The intensity in Indonesia accelerated at a very fast rate from about 0.25 kWh/1995 US$ in 1994 to 0.42 kWh/1995 US$ in 2002. In the Maldives, the electricity intensity is the lowest but shows an increasing trend.

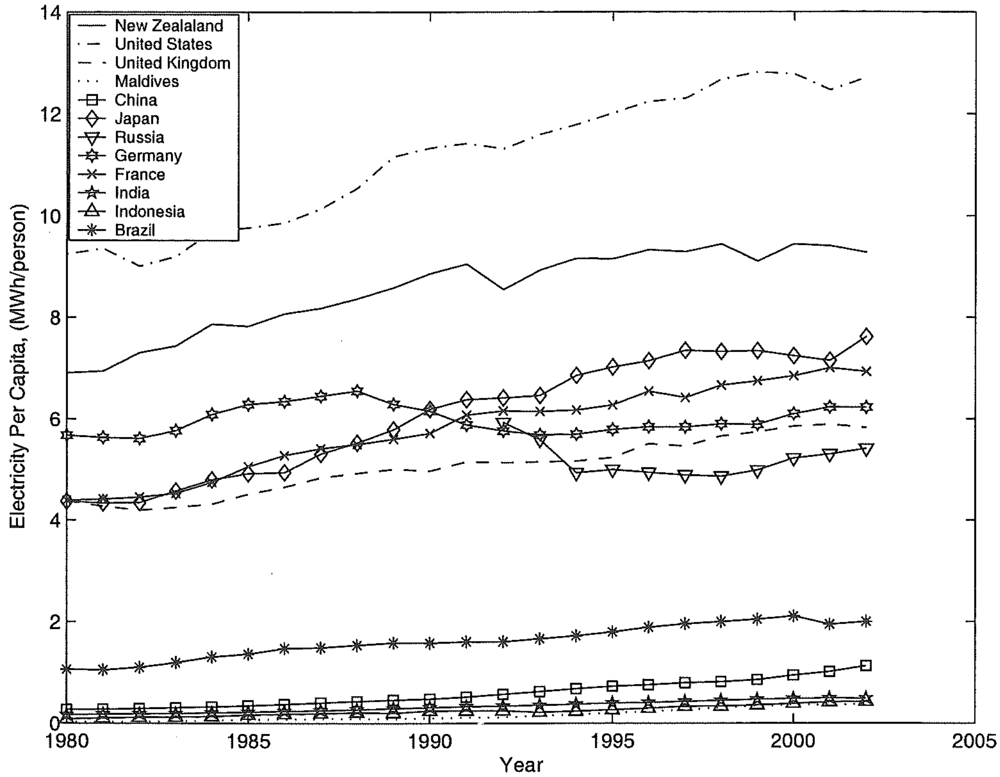

Figure 2.2 Electricity per capita for the 12 countries

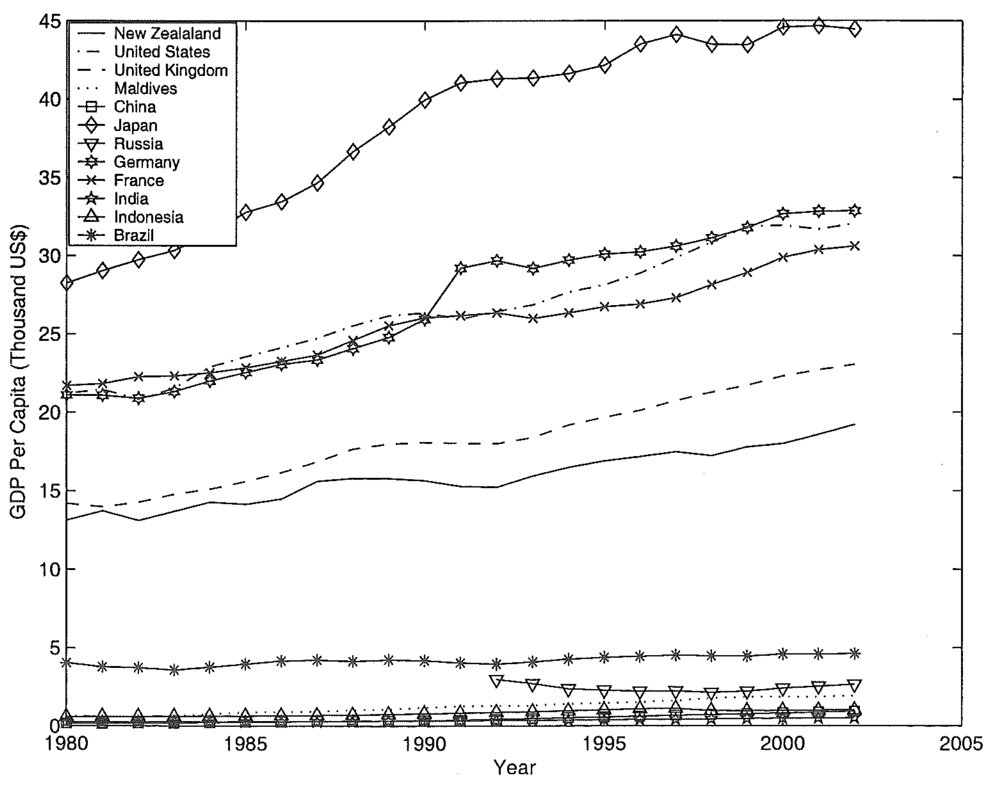

Figure 2.3 GDP per capita for the 12 countries

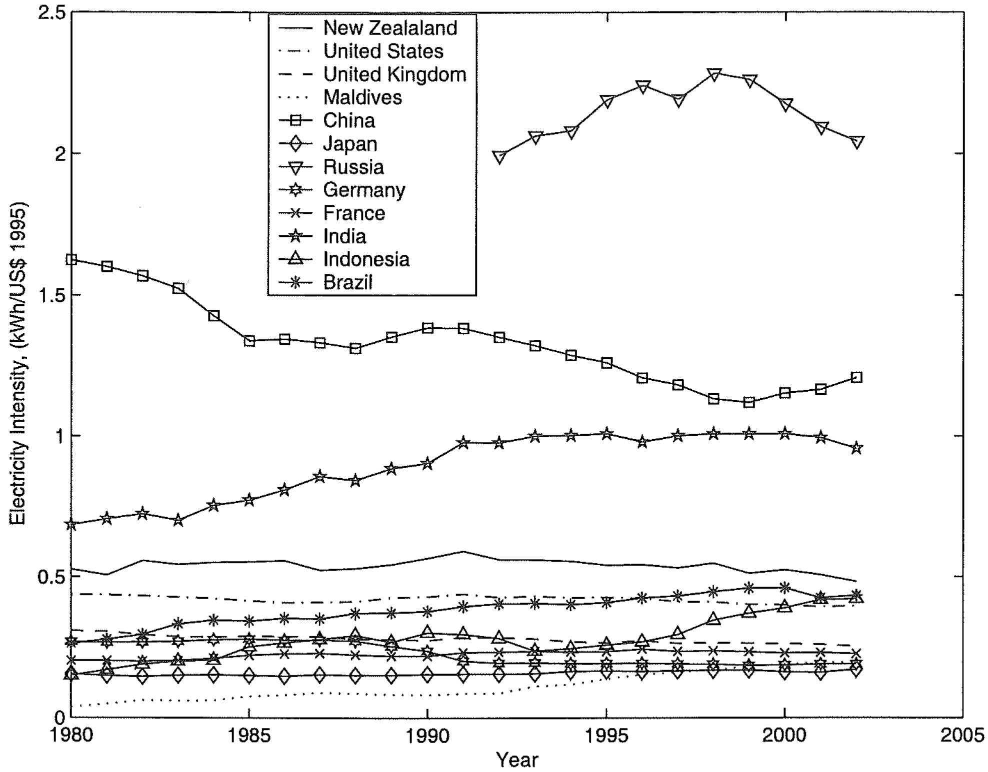

Figure 2.4 Electricity intensity in the selected countries

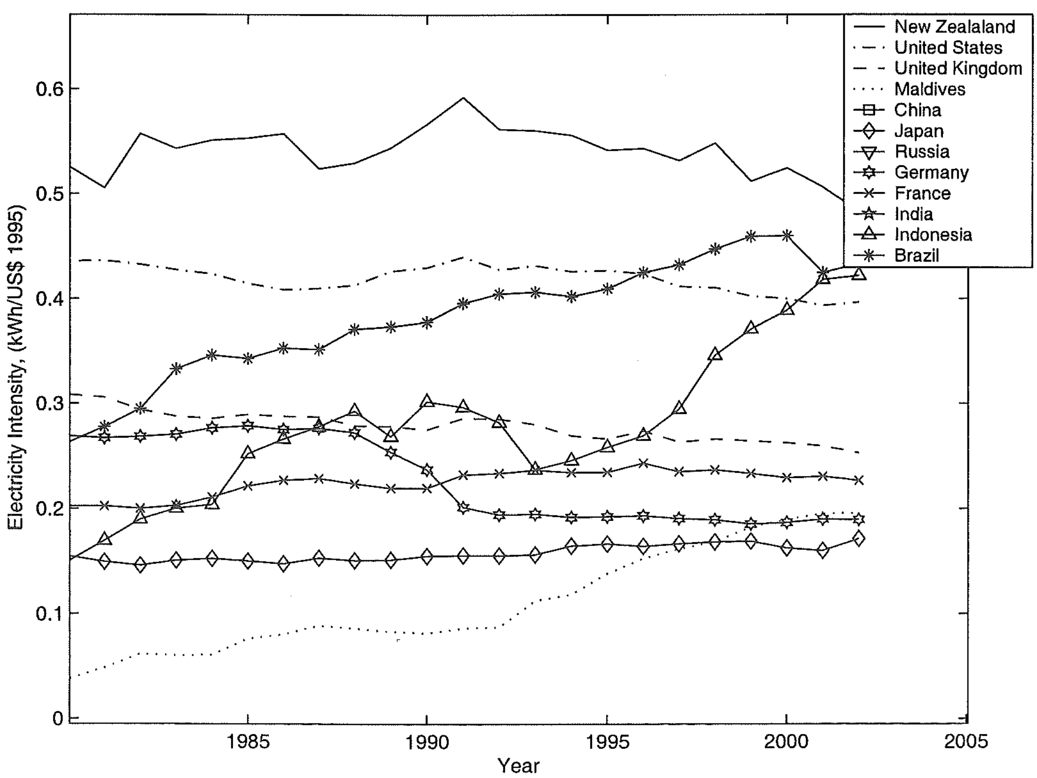

Figure 2.5 Lower section of Figure 2.4 enlarged

The electricity intensity curves for the 12 countries are shown in Figure 2.6. The curves are spread out along the two axes. There is a distinguishing pattern in the curves of the industrialised countries and the developing countries. The industrialised countries with high income per capita generally have low consumption per dollar of GDP. Therefore these plots are towards the lower right portion of Figure 2.6. The developing countries with low income per capita have low to high level of consumption per dollar of GDP. These are on the left portion of Figure 2.6. It is useful to analyse the two groups separately.

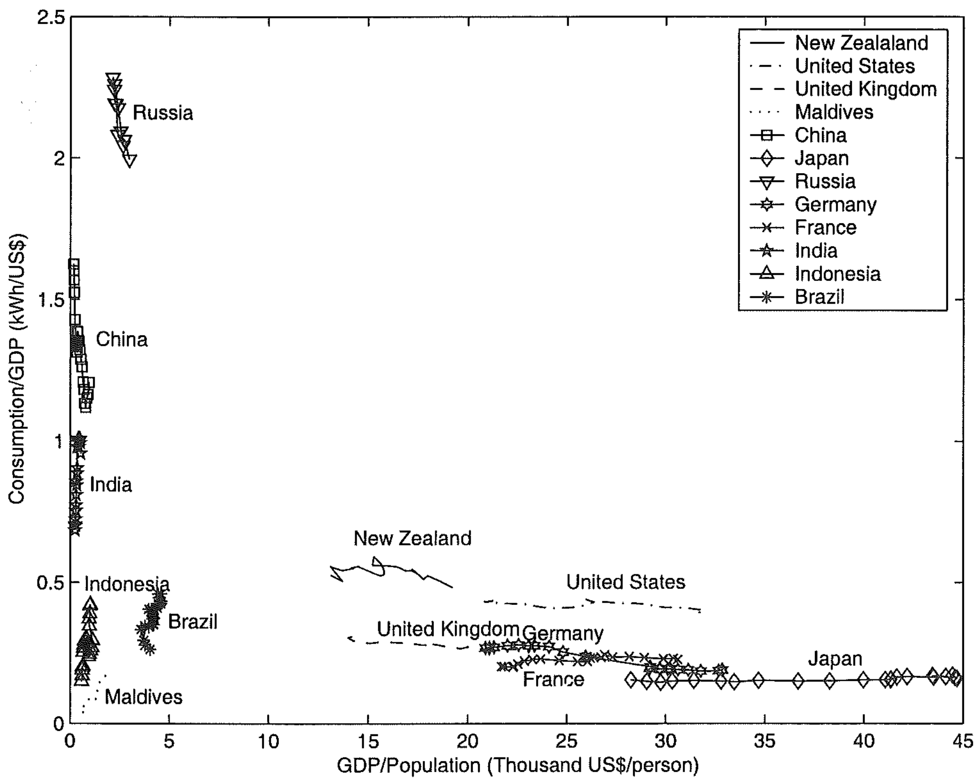

Figure 2.6 Electricity intensity curves for the selected countries

Figure 2.7 and 2.8 shows the electricity intensity curves for the industrialised countries and the developing countries respectively. The electricity intensities for most of the industrialised countries have declined relative to economic growth except for France and Japan. In France the electricity intensity has grown slightly relative to economic growth and is steady in the later years. Japan shows a more steady level of electricity intensity with economic growth. In the developing countries, the electricity intensity in India initially increased relative to economic growth, levelled out around 2000 and began to decrease after this. In Indonesia, the intensity also initially increased, levelled and then decreased and then again increased with the growth in GDP. Even with a decline in GDP the electricity intensity in Indonesia has continued to increase. In China, the electricity intensity has decreased with the growth in GDP until 1999 and then began to increase in the later years.

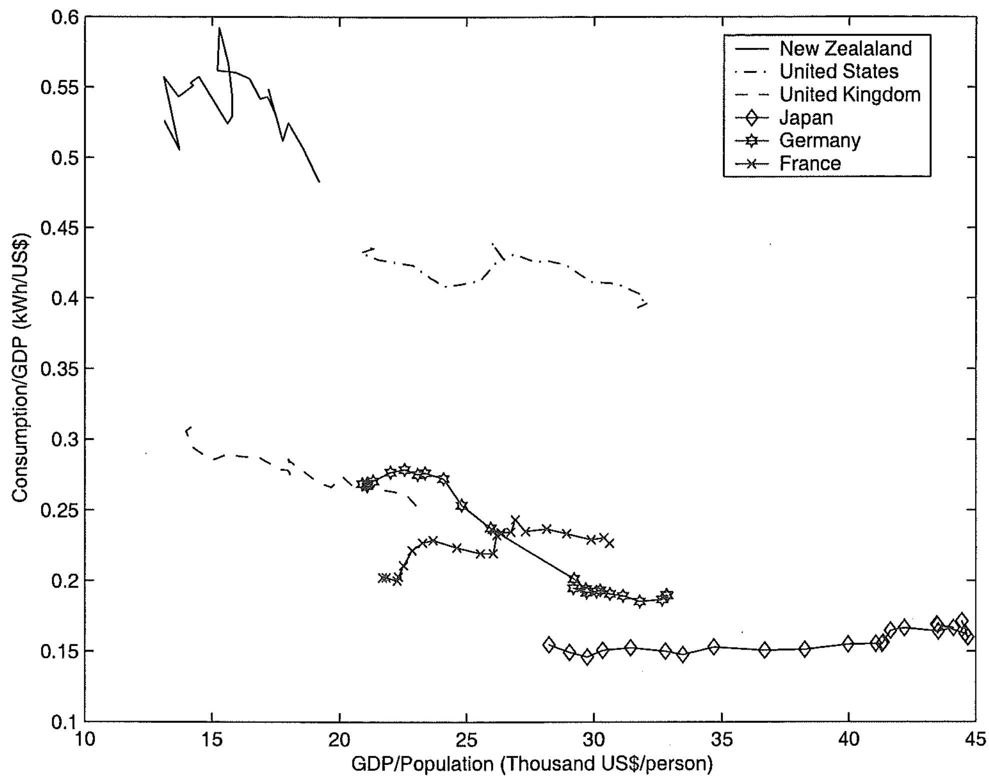

Figure 2.7 Electricity intensity curves for the industrialised countries

In Russia, the electricity intensity has initially increased with decrease in GDP until 1996 and has subsequently decreased with an increase in economic growth. In Brazil, even with periods of declining economic growth, the electricity intensity has continued to increase over the whole period. In the Maldives, the electricity intensity has increased consistently with growth in the economy.

The electricity intensity factors for the industrialised countries are shown in Figure 2.9, while those for the developing countries are shown in Figure 2.10. In general, the electricity intensity factors for the industrialised countries have decreased over the years.

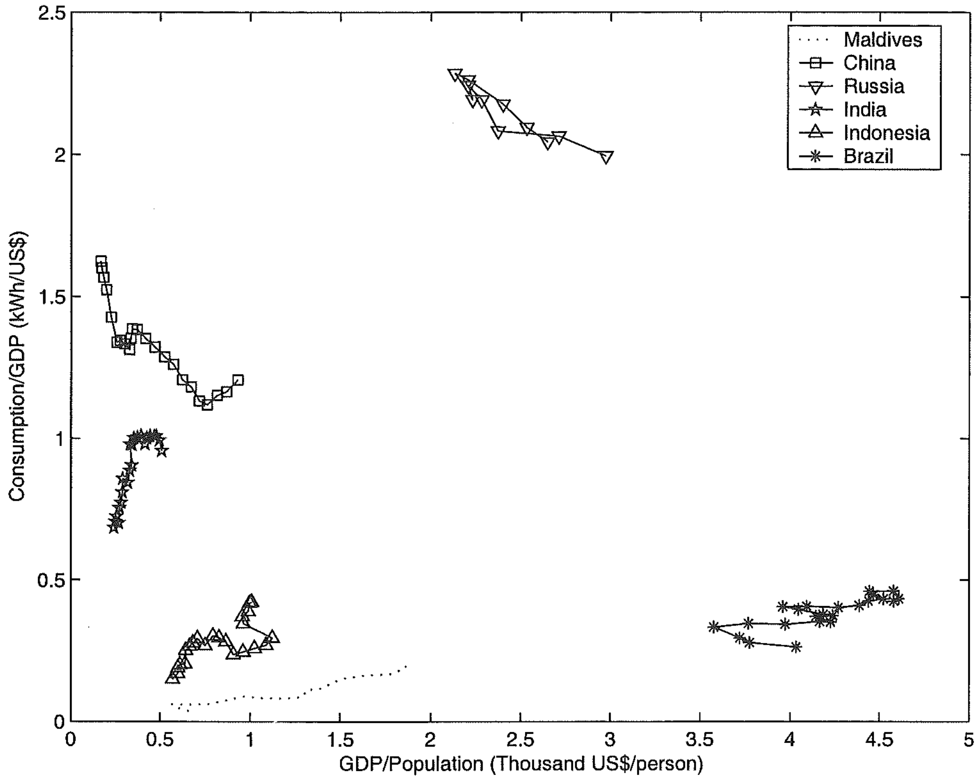

Figure 2.8 Electricity intensity curves for the developing countries

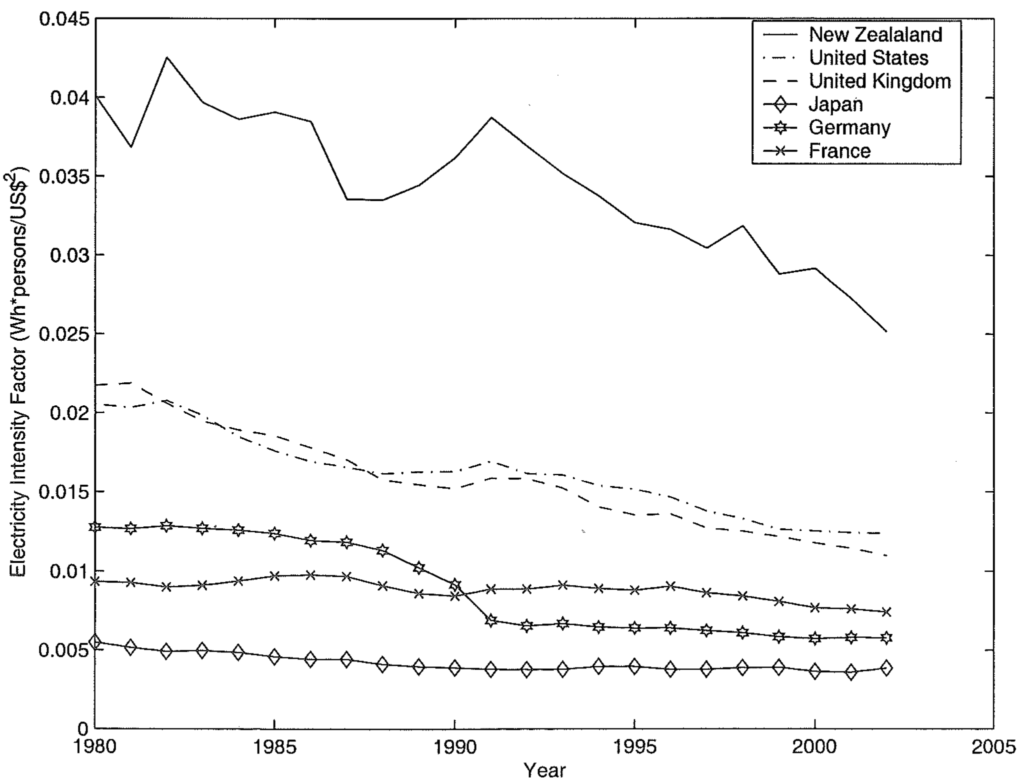

Figure 2.9 Electricity intensity factors for the industrialised countries

The electricity intensity factors for New Zealand are the highest over the whole period, while the United States and the United Kingdom have similar levels. Japan shows the lowest electricity intensity factors. The sudden drop in electricity intensity for Germany from 1992 is because electricity consumption data for Germany after 1992 includes those for East and West Germany. However the GDP data for East Germany prior to 1992 was not available[1]. Therefore, the GDP data for Germany before 1992 is less than it should have been due to the unavailability of this data. Overall, for the industrialised countries the electricity intensity factors are converging.

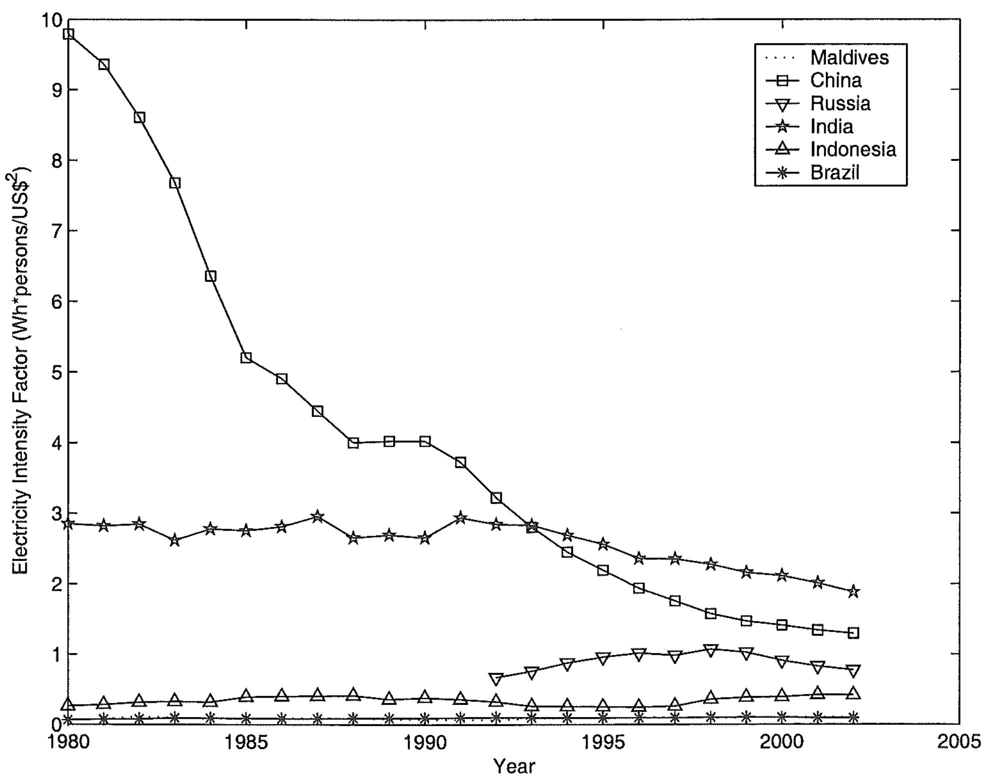

Figure 2.10 Electricity intensity factors for the developing countries

In China, the electricity intensity factor has decreased dramatically from 9.8 (Wh/US$^{2}) in 1980 to 2.2 (Wh/US$^{2}) in 2002. In India, the factor has decreased slightly over the years. In Russia, the factor has initially increased slightly, peaked around 1998 and decreased slightly following the peaked period. Overall the electricity intensity factors appear to be converging in a similar manner to those for the industrialised countries.

[1] The data is not available from the source of data used for this research [EIA_2, 2004].

2.3.2 Discussion

It has been observed that the electricity intensity and thus the electricity intensity curve and electricity intensity factors are higher for New Zealand than the other industrialised countries. The high electricity intensities in some countries have been explained with regard to availability of inexpensive hydro capacity [Nilsson, 1993]. Table 2.1 lists the percentages of electricity generated by type for the 12 countries [EIA_2, 2004].

Table 2.1 Percentage electricity generation by type at 2001

Country	Thermal	Hydroelectric	Nuclear	Other
New Zealand	33.9	55.0	0.0	11.2
United States	71.6	5.6	20.6	2.2
United Kingdom	73.6	1.1	23.7	1.6
Maldives	100.0	0.0	0.0	0.0
China	80.3	18.3	1.2	0.1
Japan	58.9	8.5	31.0	1.6
Russia	64.1	20.6	14.9	0.4
Germany	62.5	3.7	29.7	4.1
France	8.4	14.1	76.8	0.7
India	82.6	13.4	3.3	0.6
Indonesia	86.1	11.0	0.0	2.9
Brazil	9.4	82.1	4.4	4.1

Hydroelectricity accounts for 55% of the total electricity generated in New Zealand whereas the next competing industrialised country, France, has only 14% of its total electricity generated using hydropower. Therefore, it can be concluded that the high electricity intensity in New Zealand can be partly explained by the availability of cheap hydroelectricity in the country. On the other hand the other industrialised countries have significant percentages of nuclear power, whereas the developing countries have little.

The high electricity intensity in New Zealand relative to other industrialised nations may also be the result of high electricity consumption in residential homes. In general, electricity is used for all residential purposes including water heating, air conditioning and cooking. The 1981 census indicated that 92 percent of homes in New Zealand have electric hot water heating, 73 percent have predominantly electric space heating and 92 percent use electric stoves for cooking [Ministry of Energy, 1982]. In many of the developed countries natural gas is used for water heating, space heating and cooking. Therefore, the electricity intensity in New Zealand would be higher than the other countries. It could also be due to the electricity intensive industries (EIIs) in New Zealand such as aluminium smelter, steel, pulp and paper mills.

Electricity prices and relative fuel prices play an important role in locating electricity intensive industries, and the choice of energy carrier and space heating [Nilsson, 1993]. However it has been found that the electricity price does not affect electricity efficiency significantly in the household and service sectors [Nilsson, 1993]. This was supported by the fact that the energy intensities in several countries have continued to decrease when energy prices have been falling.

Several key factors are expected to affect the shape of the industrial electricity intensity [Meyers and Sathaye, 1989]. For example, if there is a change in the structure of the manufacturing sector, it would have a substantial effect on the industrial electricity intensity. Rapid introduction of more modern and efficient factories may force down the electricity intensity. In addition, improvements in end-use efficiency through energy management and the introduction of new equipment, also decreases the electricity intensity.

2.3.2.1 Intensity in China

The electricity intensity in China has fallen over the years. This is considered to be caused by the rising relative energy prices, research and development expenditures, and ownership reform in the enterprise sector [Fisher-Vanden and Jefferson, 2004]. In addition, the shift in China's industrial structure could have been the principal drivers of

China's declining electricity intensity and its use [Fisher-Vanden and Jefferson, 2004]. According to some analysts the fall in China's energy intensity has been attributed mainly to the decline in real energy intensity whereas others believe this has been caused by structural shifts away from more energy intensive industries. Zhang [Zhang, 2003] showed that the overwhelming contributor to the decline in industrial energy use was the decline in real energy intensities. Hirschhausen and Andres [Hirschhausen and Andres, 2000] concluded that even with higher economic growth in China, structural changes towards less electricity intensive activities will support slower consumption increases. This would result in a decrease in electricity intensity in China. However, the increase in electricity intensity for China in the last 3 years could not be explained by the increase in GDP per capita in the past years.

Shiu and Lam [Shiu and Lam, 2004] examined the causal relationship between electricity consumption and economic growth in China. Their study revealed that despite the remarkable growth in the electric power industry in the last few decades, the speed did not keep up to pace with economic growth. Capital investments in the power sector have lagged behind the economic growth [Shiu and Lam, 2004]. Demand for electricity increased tremendously during the same period as the economy developed and the living standards of people were improved. From 1970-2000, around 70-80% of the electricity consumption in China was in industrial production [Shiu and Lam, 2004]. A large share of the GDP is contributed by the industrial production, and therefore the growth in industrial electricity demand raises the real GDP of China. The strong rate of GDP growth as compared to the growth in electricity has contributed to the fall in China's electricity intensity. In addition, improvements in electricity efficiency of the electrical appliances and equipment, and conservation efforts to reduce electricity consumption have been identified as two major reasons for the fall in electricity intensity in China [Shiu and Lam, 2004]. Despite the strong growth in electricity consumption in the industrial sector of China, it has also been pointed out that the low electricity consumption per capita is affected by the fact that a large number of the rural population still have no access to electricity and some areas still face the problem of power shortages [Shiu and Lam, 2004].

2.3.2.2 Intensity in India

The electricity consumption in India has increased nine times from 1970 to 2000 [Reddy and Balachandra, 2003]. Beside population and economic growth, efficiency of energy utilisation has been a major factor that influences energy demand [Reddy and Balachandra, 2003]. However, during 1980-2000 India has achieved its highest economic growth at a rate of 6% per annum [Reddy and Balachandra, 2003]. This may have contributed to the slow growth in electricity intensity, and thus the electricity intensity has declined in the last few years. It has been found that the industrial sector, that consumes more than half of the total energy in India, is relatively inefficient in its energy use [Reddy and Balachandra, 2003]. The government of India has conducted several programmes to reduce the energy use in the energy intensive sectors such as foundry, re-rolling mills, glass and ceramics in the later half of the 1990s [Subrahmanya, 2004]. These programmes might also have contributed to the decline in electricity intensity in the last few years.

The increase in electricity intensity of India in the initial years can also be explained as follows. With the advancement of the Indian economy, the conventional fuels such as coal, firewood and oil were substituted by electricity [Ghosh, 2002]. High disposable incomes in households have made them more dependent on electric gadgets for recreation and comfort [Ghosh, 2002]. Electricity consumption in the industrial and commercial sectors has been used as the basic energy input due to its clean and efficient nature [Ghosh, 2002]. The electricity consumption growth in these years is therefore faster than the economic growth. This has resulted in an increase in intensity. It has been found that electricity conservation policies in India can be initiated without deteriorating economic side effects [Ghosh, 2002]. This suggests that the energy conservation and efficiency program that has been planned [Ghosh, 2002] would result in a further decline in electricity intensity in India.

2.3.2.3 *International Level Comparisons*

Several studies on energy intensity and electricity intensity have been carried out that compare the intensities at an international level. A study of these may explain the behaviour of the intensity patterns for the countries presented in this chapter. Sun [Sun, 2002] analysed the decrease in energy intensities between the Organisation for Economic Co-operation and Development (OECD) countries from 1971 to 1998. This reflected strong signs of new technology and advanced social structures within the countries. These factors have transferred from one country to the other to enhance productivity and improve energy efficiency, or have helped to achieve a peak level of energy intensity in other countries [Sun, 2002].

Fatai *et al.* [Fatai *et al.*, 2004] examined the causal relationship between energy consumption and GDP in New Zealand, Australia, India, Indonesia, The Philippines and Thailand. They found evidence of a unidirectional link from real GDP to industrial and commercial energy consumption and to aggregate final energy consumption in New Zealand and Australia. For India and Indonesia, a unidirectional link from energy to income was established. The difference between the developed countries and developing countries could be explained by the role energy plays in the respective economies. It was found that the energy intensive industries in the developing countries played a larger role in production than in the developed countries [Fatai *et al.*, 2004].

Worrell *et al.* [Worrell *et al.*, 1997] examined the energy intensity in the iron and steel industry of seven countries including Brazil, China, France, Germany, Japan and the United States. Iron and steel industries in these countries are one of the largest energy using and most energy-intensive industrial sub-sectors [Worrell *et al.*, 1997]. In Brazil, it was found that investments in energy efficiency were low during the first half of 1980s due to economic uncertainties in the country. This has resulted in an increase in electricity intensity in the 1980s (Figure 2.4 and 2.5). In the late 1980s the country began with long term investments in modernisation of plants (including new investments in energy efficiency) along with the beginning of the privatisation of the steel industry [Worrell *et al.*, 1997]. The effect of these long term efforts may be the factor that contributed towards a decrease in electricity intensity for Brazil during the latter years. In China, several energy efficiency programs between 1980 and 1990 for the heavy industries have resulted in strong reductions in sectoral energy consumptions (SEC) [Worrell *et al.*, 1997]. In France, energy and electricity intensity increased in the early 1980s (Figure 2.5). However, SEC decreased slightly in France as a result of structural change towards more secondary steel [Worrell *et al.*, 1997]. In Germany a small shift towards less energy-intensive products are observed [Worrell *et al.*, 1997]. Some important energy efficiency measures such as increased recovery of basic oxygen furnace (BOF) converter gases, closing of last open hearth furnace (OHF) capacity, increased use of pellets as blast furnace feed, increased electricity production through top gas recovery turbines at the blast furnaces, and heat recovery at electric arc furnaces (EAF) and sinter plant furnaces helped to maintain and slightly reduce the intensity in Germany [Worrell *et al.*, 1997]. In Japan, the most significant contribution to energy saving was achieved through the increase in continuous casting from 59% in 1980 to 94% in 1991 [Worrell *et al.*, 1997]. In the United States, the decrease in SEC was contributed by both the structural change and efficiency improvement [Worrell *et al.*, 1997]. This has helped to gradually decrease the electricity intensity over the years.

Dincer [Dincer, 1997] analysed the energy intensity for all OECD countries. A decline or relatively stable energy intensity was generally observed for all countries. This is caused by technological advances leading to improvements in energy efficiency and structural changes towards less energy intensive industries [Dincer, 1997]. However, it was found that the rate of decline in the recent years is less than those observed in the past years. These changes are caused by numerous underlying factors such as technological changes, demographic changes, substitution effects, composition mix of the national output and sources which contribute to the total factor productivity of an economy [Dincer, 1997].

The energy intensities of Brazil, China and India have also been compared by Focacci [Focacci, 2005]. Although these developing countries are not reciprocally homogeneous, their economic systems are based on similar pillars including fast growing GDP rates, sound industrial bases, remarkable manufacturing exports and consolidated traditions in raw material exports [Focacci, 2005]. An increasing energy intensity trend was observed for Brazil and India, while a decreasing trend was observed for China [Focacci, 2005]. This trend of energy intensities is similar to the electricity intensity patterns for these countries (Figure 2.4). As for developed countries, it was found that the economic growth is not separated from a higher energy demand for these developing countries [Focacci, 2005].

The electricity industries in the industrialised countries appear to have gone through the growth phase and are either at the mature or ageing phase. However, the electricity industries in most of the developing countries appear to be more in the growth phase or approaching maturity, except for Russia and China. The convergence of electricity intensity factors towards similar values generally suggests similar levels of efficiency achievements especially through modernisation of electricity intensive equipment. Some past studies on energy use have shown that the energy intensity paths of both developing and industrialised countries seem to converge towards a common pattern of energy use with a decreasing trend by the industrialised countries and an increasing trend by the developing countries [Nilsson, 1993] [Mielnik and Goldemberg, 2000]. Many complex issues that surround these discussions and parts of the behaviours have also been explained [Cohen *et al.*, 2005]. For example, the developing countries concentrate on increasing their export industries in the energy-intensive segments of the economy and an important component of the energy consumed in these industries is being shipped outside those countries, embodied in exports of manufactured and other goods [Schaeffer and de Sa, 1996] [Machado, 2001]. A real closing of the gap between the richer and poorer countries of the world has also been observed [Birol and Argiri, 1999].

Further studies at country level comparisons can also be found in the literature. For example, while studying the electricity consumption in the accommodation sectors of New Zealand [Becken *et al.*, 2001], it was reported that an optimistic trend of decoupled growth in GDP and energy demand was observed [EECA, 2000]. This suggests declining energy intensity and perhaps explains the similar pattern observed for the electricity intensity of New Zealand. A study by Doms and Dunne [Doms and Dunne, 1995] reported a steady decline in overall energy intensity in the United States manufacturing industry at a time when the share of electricity in the total energy consumption rose sharply.

Furthermore, a study by Nagata [Nagata, 1997] reported that the United States consumes more energy than Japan even when the non-technological factors are taken into account and it was expected that the potential for energy conservation was higher for the United States than Japan except for freight movement. In studying the energy intensity in the manufacturing sectors of some countries including the United States, Germany, the United Kingdom, France and Japan, it was concluded that the major reason for the inter-country differences in the intensity appears to be the nature of processing carried out by each country [Theriault and Sahi, 1997]. Some countries concentrate on primary processing (pulp and paper production) which is more energy intensive as compared to other countries that concentrate on secondary processing (paper products and printing) [Theriault and Sahi, 1997]. There are many other studies relating either energy consumption or electricity consumption to economic growth at country levels or international levels [Jenne and Catell, 1983] [Gunn, 1997] [Priambodo, 2002] [Bhattacharyya and Ussanarassamee, 2003] [Tunc *et al.*, 2004] [Hessari, 2004].

2.4 INTENSITY IN THE REGIONS

2.4.1 Results

The relationship between electricity consumption and economic growth at regional levels of the world are examined. Figure 2.11 shows the electricity consumption per capita for the regions of the world and the world total, while Figure 2.12 shows the corresponding GDP per capita for the regions. The electricity consumption per capita has gradually increased for all regions of the world except for Eastern Europe and the Former Soviet Union. This is mainly affected by decreases in electricity consumption due to the fall of the Soviet regime, the highest electricity consumer for this region.

As observed for the industrialised countries in the previous section, the electricity consumption per capita is highest for the industrialised regions of the world. However, the wealthiest region is not necessarily the most energy intensive. Industrialised Asia has the highest GDP per capita but it has the second highest electricity consumption per capita. The high GDP per capita in Industrialised Asia is due to the high GDP per capita of Japan (see Figure 2.3). The electricity consumption per capita is the highest for North

America throughout the whole period, while this region has the third highest GDP per capita overall. This reflects the high level of electricity consumption per capita in the United States (Figure 2.2). In the developing regions of the world, the electricity consumption per capita and the GDP per capita are just below the world average, except for the electricity consumption per capita of Eastern Europe and the Former Soviet Union which is slightly higher than the world average. The gap between the income levels of industrialised and developing regions is larger than the gap between electricity consumption.

Figure 2.13 shows the electricity intensity for the regions of the world and the world total while Figure 2.14 enlarges the lower section of Figure 2.13. The electricity intensity in Eastern Europe and the Former Soviet Union is the highest and most varying. There is a sudden decrease in the early 1990s reflecting the break up of the Soviet Union. However, even after the fall of the Soviet regime, this region has still the highest electricity intensity with a decreasing trend. Eastern Europe and the Former Soviet Union is the only region with intensity above 1 kWh/US$ (1995). The electricity intensities of Industrialised Asia followed by Western Europe are the lowest and at very constant levels over the last 20 years. The intensities of North America are near constant or decreasing but slightly above the world average electricity intensity. The other developing regions of the world reflect an increasing intensity over this period. The fastest growth in electricity intensities is observed in the Middle East, which is the third lowest in the early 1980s but is the highest in the 2000s. Irrespective of these trends, the world average electricity intensity has been at a near constant level of around 0.4 kWh/US$ (1995) for more than 20 years.

The electricity intensity curves for the regions of the world are shown in Figure 2.15. A significant gap between the income levels of industrialised regions of the world and the developing world can be observed. The curve for Eastern Europe and the Former Soviet Union is much higher than the rest. Figure 2.15 is divided into two groups for clarity. Firstly, the intensity curves for the industrialised regions are plotted in Figure 2.16. Secondly, the intensity curves for the developing regions and the world average electricity intensity, excluding Eastern Europe and the Former Soviet Union, are shown in Figure 2.17.

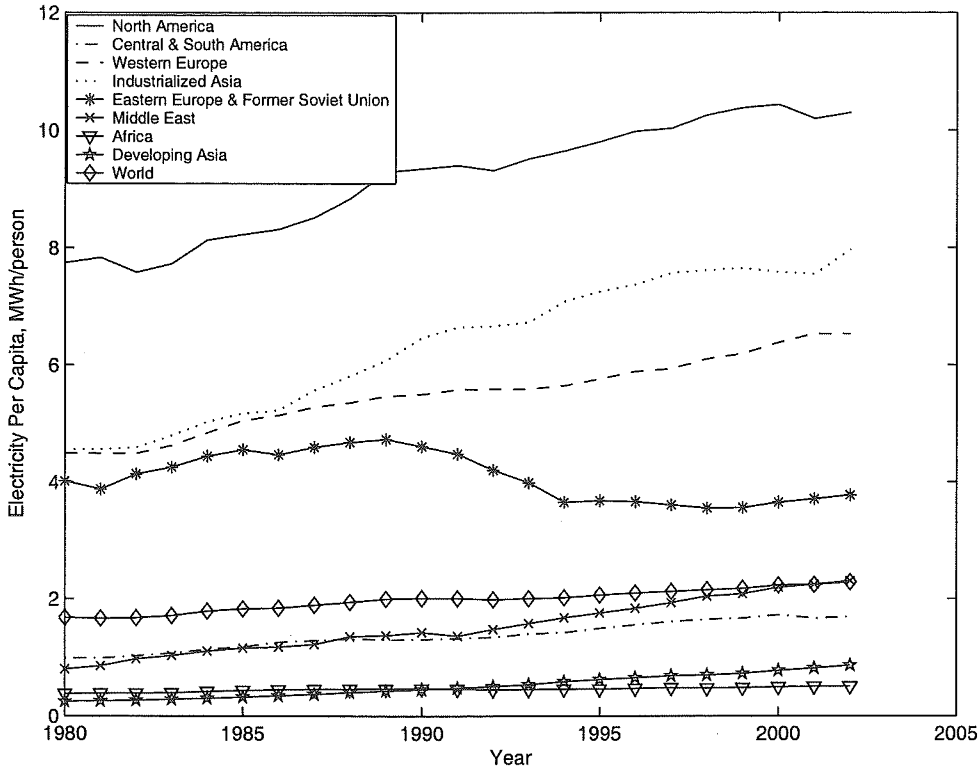

Figure 2.11 Electricity per capita for the regions of the world and world total

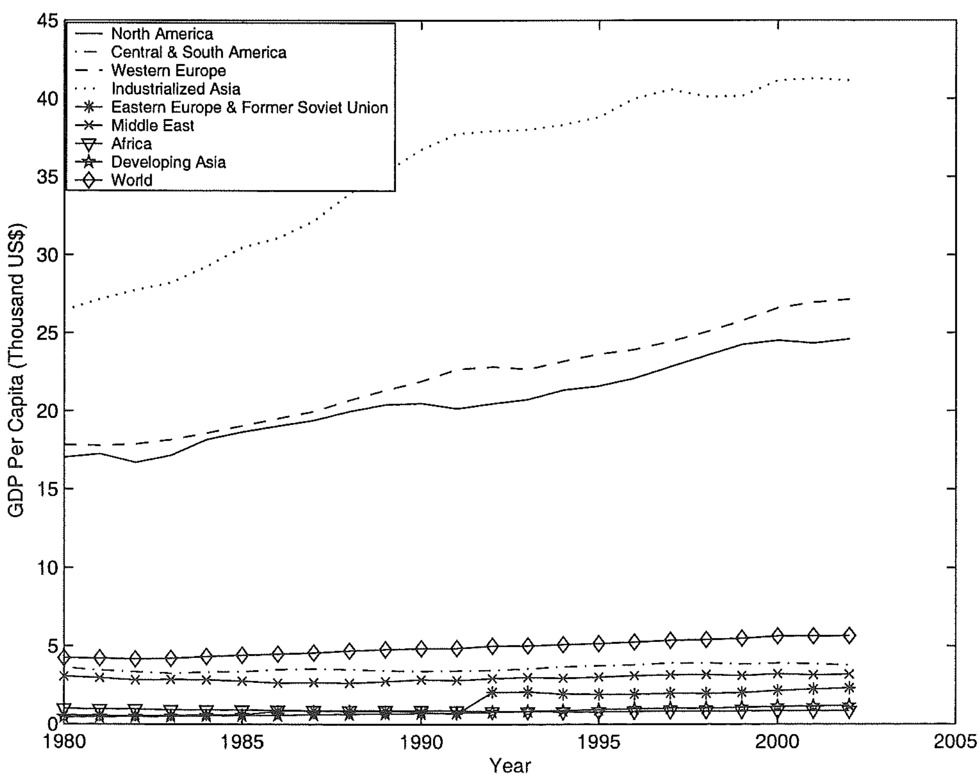

Figure 2.12 GDP per capita for the regions of the world and world total

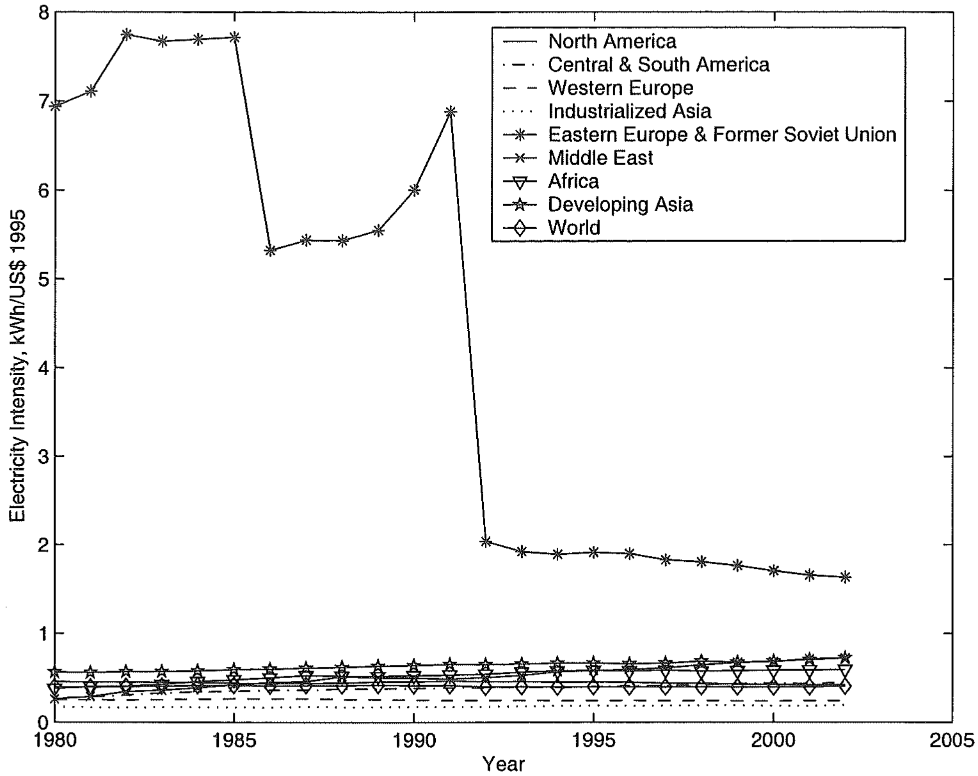

Figure 2.13 Electricity intensity for the various regions of the world

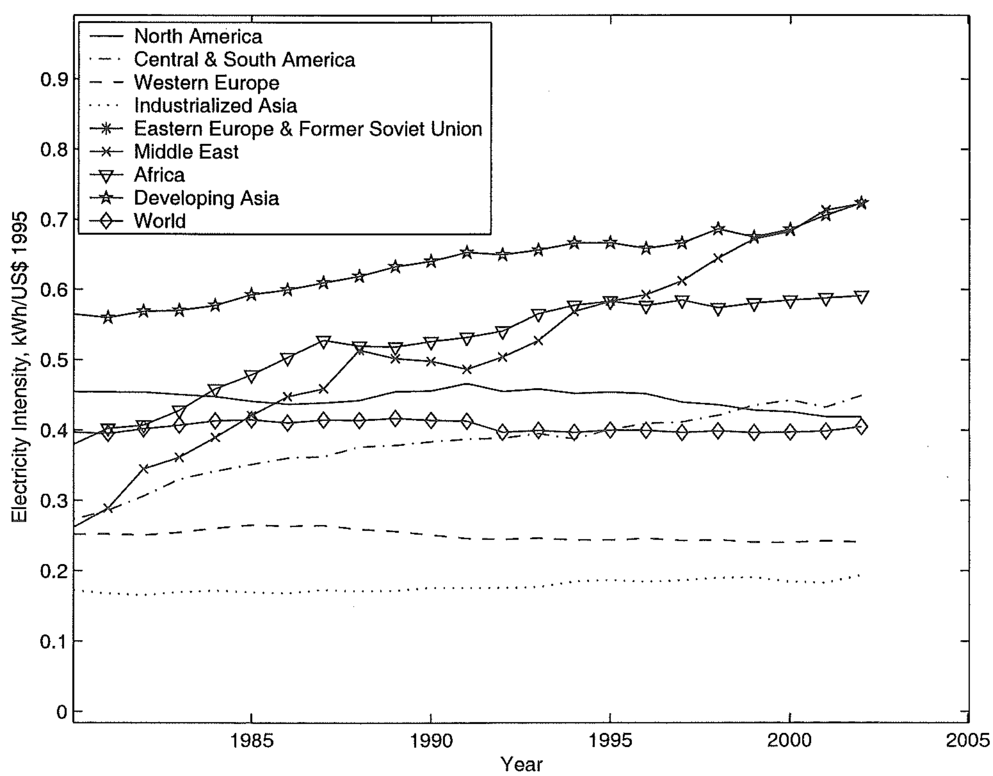

Figure 2.14 Electricity intensity for the regions (Figure 2.13 enlarged)

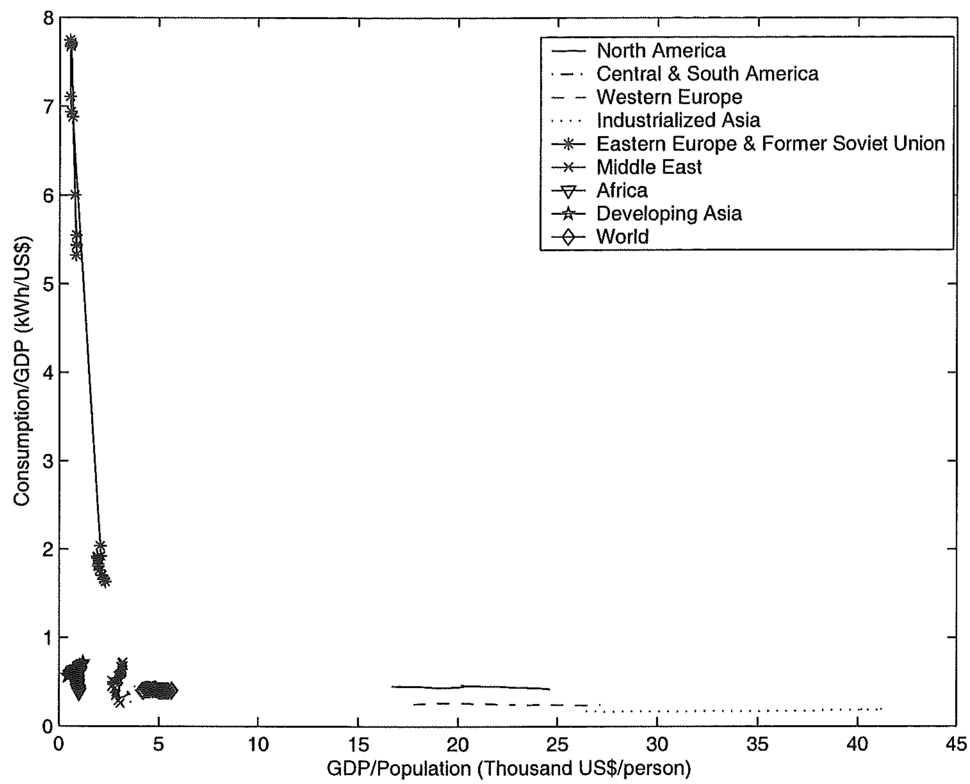

Figure 2.15 Electricity intensity curves for the regions

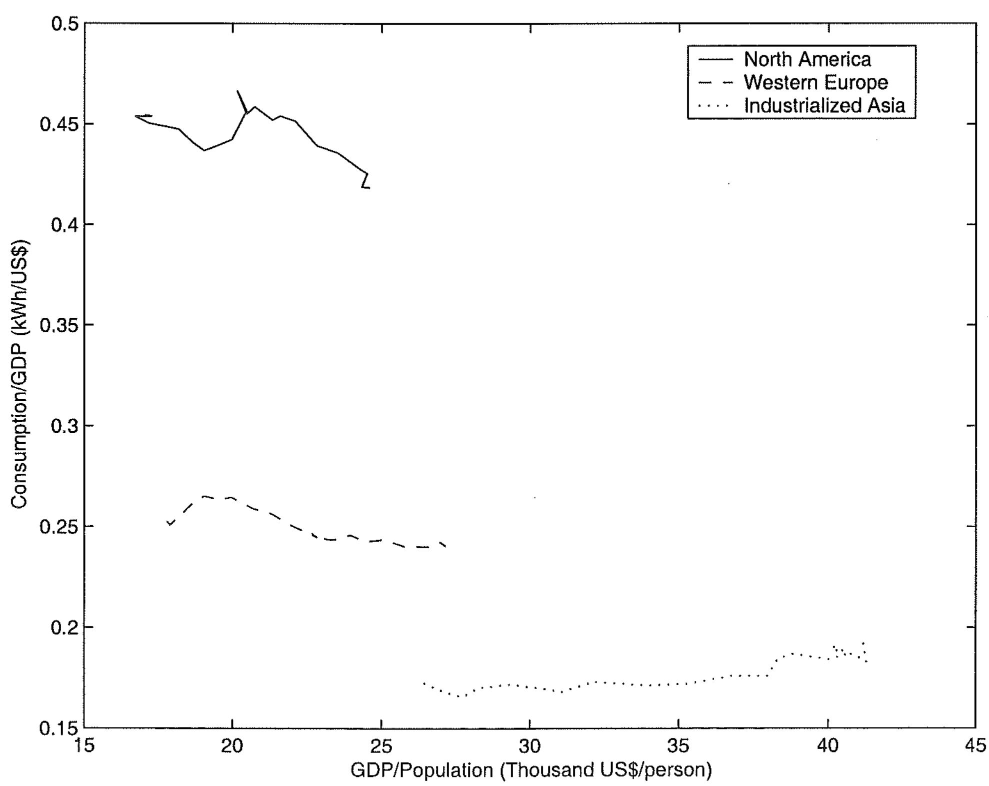

Figure 2.16 Electricity intensity curves for the industrialised regions of the world

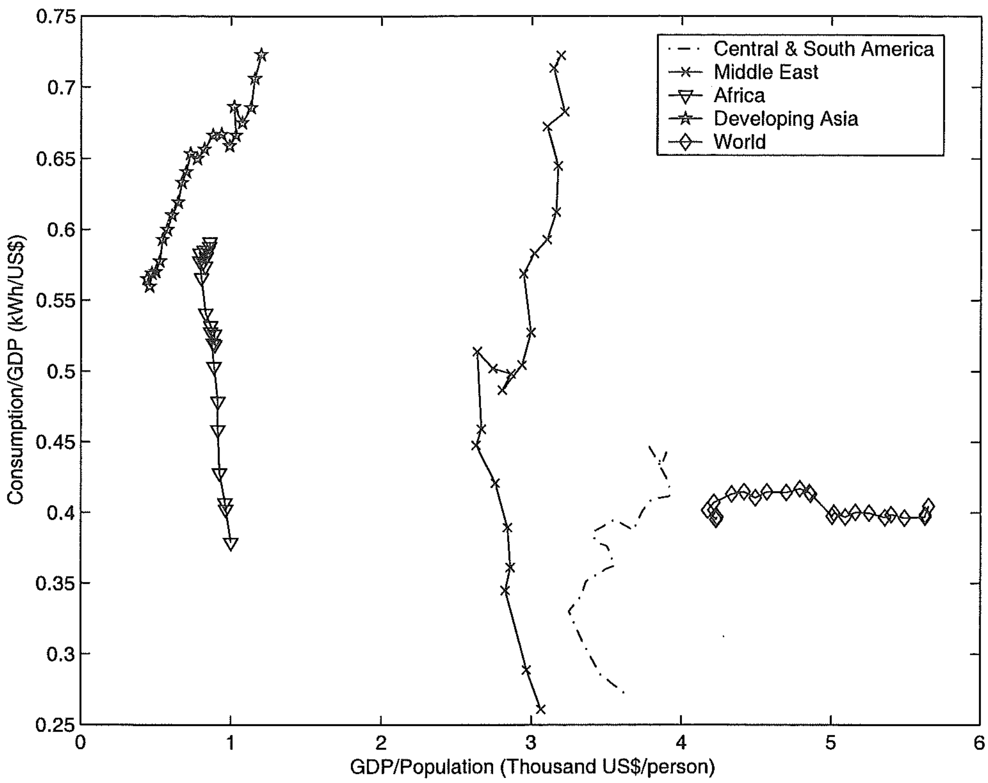

Figure 2.17 Electricity intensity curves for the developing regions of the world and world total

Among the industrialised regions of the world, North America has the highest electricity intensity but the lowest GDP per capita while Industrialised Asia is the least electricity intensive but has the highest GDP per capita. The intensity curves for Western Europe and North America appear to have gone through the growth and mature phase and are now in the ageing phase. However, those for Industrialised Asia appear to have gone through the growth phase and are now in the mature phase.

In the developing regions, there appears to be little variation in GDP per capita as compared to the changes in electricity intensity. The electricity intensity in the developing regions has grown at a much faster rate than the growth in GDP per capita. Therefore, the intensity curves appear mostly vertical. All the developing regions show a growth phase in their electricity industries. However, the world average shows that the industry has gone through the mature phase and is now in the ageing phase.

The electricity intensity factors for the regions of the world are shown in Figure 2.18. Again the electricity intensity factor for Eastern Europe and the Former Soviet Union is very high at the initial years. Figure 2.19 enlarges the lower section of Figure 2.18. The electricity intensity factors for Africa, the Middle East, and Central and South America are increasing while those for Developing Asia and Eastern Europe and the Former Soviet Union are decreasing over the years. The intensity factors for the industrialised regions are very low, comparable to each other and at very constant levels over the years. The intensity factors for all the developing regions are above the world average while those for the industrialised regions are below the average.

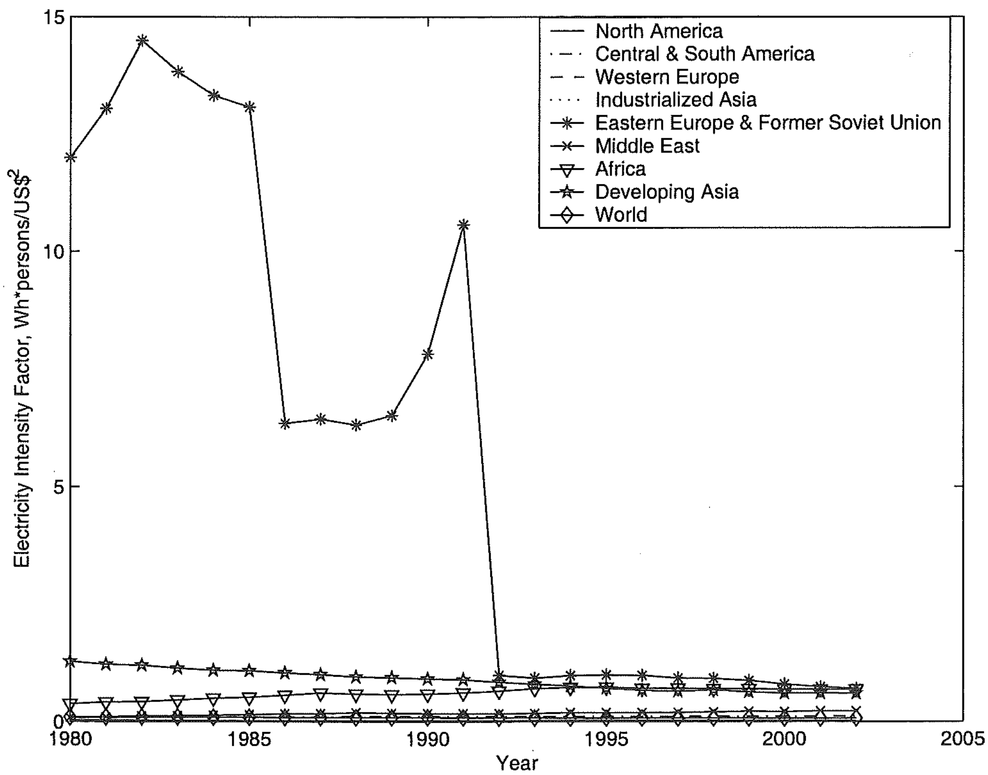

Figure 2.18 Electricity intensity factors for the various regions

2.4.2 Discussion of Results

Since the beginning of the transition of economy from a centralised planning system towards a modern free market economy, the energy consumption in Eastern Europe and the Former Soviet Union has fallen dramatically [Cornillie and Fankhauser, 2004]. Historically, the energy intensities of this region are very high. In some countries of this region, the energy intensity of industry declined sharply but the rest of the economy decreased less or remained stable as these countries moved fast on privatisation, price liberalisation and corporate restructuring [Cornillie and Fankhauser, 2004]. In some other transitional countries, the energy intensity of the industry remained constant, while those for the rest of the economy improved. In a third group of transitional countries, the energy intensity of both industry and the rest of the economy went up in the course of the transition [Cornillie and Fankhauser, 2004]. It is also believed that in these countries, privatisation and enterprise restructuring were either delayed or the privatisation process was flawed and did not result in the necessary inflow of new capital [Cornillie and Fankhauser, 2004]. Clearly, the electricity intensity of this region was also very high before the transition and is relatively very low after the transition. In addition, a decreasing trend in the electricity intensity has been observed for this region (Figure 2.13). This similarity suggests that these reasons for changes in energy intensity could have been responsible for the changes in electricity intensity in this region as well. The high energy intensities in this region have also been explained by the inefficiency of these economies and subsidised energy tariffs [Nilsson, 1993].

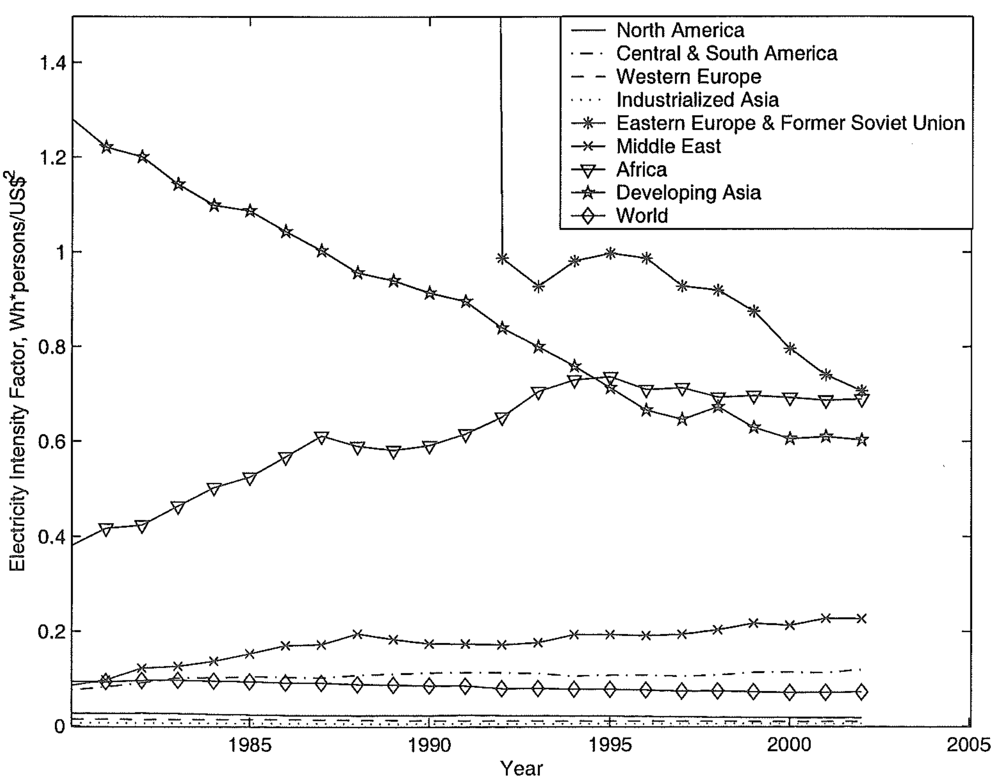

Figure 2.19 Electricity intensity factors of Figure 2.18 enlarged to show the lower section

In North America, buildings have a heating intensity some 20-30% above European levels [Schipper *et al.*, 1986]. This could have accounted for the high electricity per capita in North America compared to Western Europe (Figure 2.11). In addition, the high electricity intensity in North America compared to Europe has been explained partly due to the widespread use of air conditioning especially in USA and Canada [Schipper *et al.*, 1986]. It has also been pointed out that decreasing electricity prices increases electricity intensity in these regions [Schipper *et al.*, 1986].

It has been reported that electricity consumption in developing countries grew much faster than economic growth mainly due to the mechanisation of industrial and agricultural production and increased use of electricity in residences and other buildings [Meyers and Sathaye, 1989]. In addition, electricity has been typically sold for less than its full production cost in order to encourage economic development and provide electricity to people who could not afford to pay the full cost [Meyers and Sathaye, 1989]. This has encouraged the growth in electricity consumption in some developing countries. A study of energy intensity by Nilsson [Nilsson, 1993] indicated that the level to which the energy is linked to GDP could be debated. Energy use in many developing countries is growing at a faster rate than economic growth, leading to higher intensities.

Comparison of energy intensities in European Union countries suggested that the aggregate energy differences in Europe are strongly influenced by the direct energy intensity effect and demand effect, without the different economic structures of the countries being an important factor in the explanation of these differences [Alcantara and Duarte, 2004]. It has been identified that the metallurgical and manufacturing sectors are the most intensive in the aggregate energy intensity [Alcantara and Duarte, 2004].

The energy intensity in the industrialised countries is expected to increase by an average of 1.2% per year in the coming years whereas that for the developing countries is expected to decrease by 1.8% per year on average [EIA_1, 2004]. It is expected that the developing economies would tend to behave more like those of the industrialised countries due to improvements in the standards of living that has been projected [EIA_1, 2004]. The link between economic growth and energy demand is strongly influenced by the stage of the development and the standard of living in a given region [EIA_1, 2004]. A relatively high level of per capita energy use can be observed for advanced economies with high standards of living. However, these economies have energy use that is generally more stable or changes very slowly [EIA_1, 2004]. In modern economies, there is a high penetration rate of modern appliances and motorised equipment. The fact that the new stock is more efficient than the old it replaced suggests that the link between income and energy demand would decrease over the years [EIA_1, 2004].

2.5 DEREGULATION AND PRIVATISATION OF ELECTRICITY

Similar to many other industries, the electricity industry around the world is changing from the traditional highly regulated industry to a competitive industry. It is expected that electric power is the fastest growing source of end use energy supply throughout the world [EIA, 1996]. Traditionally, the electric power industry was based on the theory that electric power production, transmission and distribution were natural monopolies. It was also believed that large centralised power plants were the most efficient and inexpensive means of producing electric power and delivering it to customers. Most countries relied upon state-owned monopolies to finance, construct, own and operate the electric supply network until the 1980s [Hamalainen *et al.*, 2000].

Deregulation and restructuring of the electricity supply industry is one of the most important global energy developments of the last century [Hamalainen *et al.*, 2000]. Many countries have now introduced or are in the process of introducing policies to reform their electricity supply industries. This has led to a shift from engineering-led, vertically integrated electricity industries operating on a cost-plus basis to competitive markets [Hamalainen *et al.*, 2000]. Deregulation and restructuring is a form of privatisation. The means by which privatisation is introduced varies from country to country. However, privatisation will be treated in this context as any movement toward a market-driven economy or any movement that diminishes public ownership and control and increases private ownership and control [EIA, 1996]. The methods of privatisation include the direct sale of an entire state owned company to the public, partial sale of the company to public, sale of state-owned company to another company or consortiums, deregulation, removal of subsidies and voucher schemes [EIA, 1996]. Deregulation has been the most prevalent form of energy privatisation in many parts of the world.

Deregulation of electricity has not only increased the number of players in the industry but has also changed their behaviour as well [Hamalainen *et al.*, 2000]. The supply side now needs to take into account competitors and choices available to customers before making investments and pricing decisions. On the other hand, customers will be aware of the saving opportunities due to the flexibility in supply. The flexibility allows customers to choose the best deal that best fits their needs [Hamalainen *et al.*, 2000].

2.5.1 Underlying Factors for Restructuring of Electric Power Industry

The means by which deregulation and privatisation is introduced in a country varies from one country to the other. In a similar manner, the reasons for restructuring are numerous and also vary from country to country [EIA, 1996]. Some of the most common reasons include [EIA, 1996];

- Raise revenues for the state through asset sales
- Acquire investment capital
- Improve managerial performance
- Move toward market-determined prices
- Transfer technology
- Reduce the frequency of power shortages
- Reduce the cost of electricity to consumers through efficiency gain
- Take advantage of creating national and regional power grids, and
- Re-think whether electricity generation in today's economy constitutes a natural monopoly.

A range of measures have been introduced to stimulate competition in the electricity markets through privatisation of electricity assets, attracting foreign investments, separating the ownership of generation, distribution and marketing, creating electricity trading agreements (pools) and retail competition, establishing independent system operators, deregulating electricity prices and opening access to the national grid [McGovern and Hicks, 2004].

2.5.2 Historical Trends towards Privatisation

In this section, the effort made by the selected countries towards privatisation of the electricity industry is discussed very briefly. The selected countries are the 12 countries for which the electricity intensity has been examined in this chapter.

2.5.2.1 New Zealand

New Zealand began with the process of deregulating its electric power industry in 1987 aiming to transform the country to a greater free-market economy. In 1993, a transmission corporation was created and monopolies in local distribution and retailing were eliminated [EIA, 1996]. A new electricity policy designed to create competitive electricity market was also issued in 1995. The history of electricity industry and deregulation in New Zealand will be discussed in detail in Chapter 5.

2.5.2.2 United States

In 1992, the United States Congress passed the Energy Policy Act (EPACT) to promote competition in the electricity market [EIA, 2000]. As a result, retail sales in electricity markets occurred in 11 States in 1998 [EIA, 2000]. By July 1, 2000, 24 States and the District of Columbia had passed legislation or issued regulatory orders to restructure the electric power industries within their borders. Detailed history of the deregulation process in the United States is discussed elsewhere [EIA, 2000].

2.5.2.3 United Kingdom

The United Kingdom's electric utility industry privatisation efforts have been the first, largest, and most ambitious thus far among the developed countries [EIA, 1996]. Privatisation in the United Kingdom began in 1990 and was completed in July 1996 [EIA, 1996]. More details regarding the history and privatisation of electricity in the United Kingdom will be discussed in Chapter 9.

2.5.3.4 Maldives

The electricity supply in the Maldives is entirely under the control of the state-owned enterprise, State Electric Company Limited (STELCO) [STELCO, 2004]. STELCO is responsible for generating and supplying electricity throughout the Maldives. In some of the rural islands the respective local communities generate and distribute their own electricity. Due to the small size, population, economy and distribution of the country, any move towards privatisation is unlikely in the near future.

2.5.2.5 China

In order to meet the strong growth in electricity, China has begun a restructuring process. This allows private investments in the electric power industry. The State Power Corporation was divided into five generating units and two transmission companies in December 2002 [EIA_1, 2004]. The regulatory functions have also been assigned to China Electricity Regulatory Commission. However, the two largest privatised electricity generators, Huaneng Power and Beijing Datang Power, are still majority-owned by the government [EIA_1, 2004]. Efforts to liberalise electricity in China include the introduction of limited price competition. In order to set up regional power markets, stimulated electricity price competition began in early January 2004 [EIA_1, 2004]. It is hoped that this will help to end provincial trading barriers and increase reliability of supply.

2.5.2.6 Japan

The electric power sector in Japan is already privatised. However, competition from independent power producers is discouraged as 10 privately owned regional utilities produce 75 percent of the country's electricity and control the transmission and distribution infrastructure [EIA_1, 2004]. Little incentive has been offered for price competition. Electricity prices in Japan have remained high due to the lack of competition, strict government regulation, scarcity of indigenous natural resources, and high land and operating costs [EIA_1, 2004]. However, the Japanese government has begun with the process of liberalising electricity trading for large customers. It is expected that a number of companies will launch a wholesale electricity market in 2004 that will be open to large-scale industrial users.

2.5.2.7 Russia

A decentralisation program began in Russia in 1993 that will allow 75 per cent of its generating capacity to be under the responsibility of regional power companies [EIA, 1996]. The Russian government opened a new wholesale spot market in 2003 where electricity can be traded at free market prices [EIA_1, 2004]. The privatisation and overhauling of the Russian electric power sector is aimed at gaining private and foreign investment in the sector over the long term [EIA_1, 2004]. It is expected that the electricity market in Russia will be fully deregulated by 2006 [EIA_1, 2004].

2.5.2.8 Germany

Germany opened wholesale and retail competition in 1999 [EIA_1, 2004]. As a result, in 2000 power prices were around 26 percent lower than those in 1995. Even with the additional costs of the country's ecological tax and laws supporting renewable energy use and combined heat and power (CHP), residential power prices also fell by 8 percent [EIA_1, 2004].

2.5.2.9 *France*

Among the European countries, the liberalisation of electricity markets in France is the slowest. Although the country has opened 30 percent of its electricity market to competition, only 5 percent has third party access agreements [EIA_1, 2004]. The state-owned Electricite de France (EdF) owns the national grid and supplies 87 percent of all French electricity, making competition in the electricity market difficult [Global Insight, 2003]. However, the French Commission de Regulation de l'Enegise announced in January 2004 that electricity distributors must start testing their computer systems by April 2004 in order to prepare for open retail markets [EIA_1, 2004].

2.5.2.10 *India*

The Indian government is moving toward allowing 100 percent foreign ownership of generating plants. By 1995, the central government had opened eight power plants to foreign investors [EIA, 1996]. Currently, India is running 8 percent deficiency in needed electricity supply [EIA_1, 2004]. Even though private investments in the electric power sector are allowed, increasing capacity through foreign investment is difficult as many foreign investors find the country's bureaucracy onerous [EIA_1, 2004]. In 2003, most of the country's electricity sales and over half of the country's capacity were under the control of state electricity boards [EIA_1, 2004].

2.5.2.11 *Indonesia*

The Indonesian government announced in 1990 that it would actively encourage private and foreign investment in power generation [EIA, 1996]. In September 2002, the Electricity Business Act was enacted in an effort to satisfy foreign investors' desire for reform in the sector [EIA_1, 2004]. It is hoped that the legislation will eventually end the state monopoly over power generation and sales. It will also allow the separation of generation, transmission and distribution in the country. This law also allows competition that may begin anytime after 2007 [EIA_1, 2004].

2.5.2.12 Brazil

In 1993, the Brazilian government passed a law that allows large electricity consumers to build and operate their own generating facilities and sell excess power to a public utility [EIA, 1996]. The Cardoso Administration started the restructuring and privatisation of the electricity sector in Brazil in 1995 [EIA_1, 2004]. As a result, a wholesale electricity market named Merado Atacadista de Energia Electrica (MAE) was established. At present some 60 percent of electric power distribution is in the private sector [EIA_1, 2004].

2.5.3 Impacts of Privatisation

As opposed to the many advantages that motivate privatisation of electricity industry there seems to be several concerns raised regarding privatisation. Generally, privatisation was supported by those who were convinced that it would end monopolistic pricing, harmonise tariffs, enforce higher levels of efficiency, and turn electricity from a commodity into a market-driven choice of differentiated products and services [Boscheck, 1994]. However, it has been cautioned for technical, operational and co-ordination reasons and that certain types of change would probably change the special nature of the electricity industry. It has been argued that competition would merely shift income along the electricity supply chain instead of providing welfare gains for all, resulting in unfair treatment of certain consumer groups and loss of supply security [Boscheck, 1994].

It has been suggested that any move towards electricity deregulation and more reliance on market process, has enormous benefits as well as potential risks [Borenstein and Bushnell, 2000]. For example, if the move toward deregulation does not take the issue of market power seriously, it can undermine the goals of industry restructuring. Therefore, any restructuring initiative should recognise that the lack of economic shortage and price-responsive demand can produce serious market disruptions [Borenstein and Bushnell, 2000]. It was concluded that customers will benefit due to the long term gains from improved investment decisions on both the demand and supply side of the industry that is sufficient to outweigh the potential short run costs.

Andersen and Remedios [Andersen and Remedios, 2003] indicated that in the US the deregulation process has created an uneven playing field among electric utilities across the nation, and as a consequence the electric retailing market has become highly fragmented. The electricity crisis in California has earned a reputation as an incubator of bad public policy ideas [Bushnell, 2004]. Since the introduction of retail competition in 1998, electricity prices in the United States rose sharply in many states [EIA, 2000]. In addition, a series of periodic blackouts in California between 2000 and 2001 has contributed substantially to this reputation. The main factors contributing to the crisis were scarcity of generation capacity, a flawed market design and the venality of electricity production [Bushnell, 2004]. This has led many neighbouring states and countries to rethink on restructuring their electricity sectors. Those in favour of deregulation argue that their market is fundamentally different from California's, and are therefore safe from the disruptions experienced there, while the others argue that California proves that electricity restructuring is fundamentally misguided and doomed to failure wherever it is applied [Bushnell, 2004]. It is highly likely that the loss California has suffered, due to restructuring, in the last 3 years is far higher than its benefits. However, it should be noted that California is one of more than a dozen major markets that has undergone reorganisation and partial deregulation of its electricity sector, and that it has been the worst effected [Bushnell, 2004].

Large integrated power engineering companies have been established as a result of deregulation and globalisation of the power plant industry [McGovern and Hicks, 2004]. As a result of deregulation, the number of independent power producers (IPPs) increased rapidly. Minimising the capital cost and reducing the time required for constructing new power plants were the prime concerns of the new entrants to the industry. However, the IPPs faced considerable risks in the deregulated markets, as prior to deregulation state-owned utilities were responsible for financing and managing new power stations, while after deregulation the power generators sought turnkey projects and 'through-life' solutions to meet their requirements [McGovern and Hicks, 2004].

A survey of the British electricity industry showed that performance of its regulation system produced benefits, although not for all shareholders and not as fairly as possible [Oliveira and Tolmasquim, 2004]. The chosen path failed to respect intergenerational transfers as a way of fostering sustainability and equity, and therefore it has been considered unsuitable. It was also found that the system was unable to underpin simultaneous improvements in efficiency over time [Oliveira and Tolmasquim, 2004]. In addition, reforms after privatisation generally failed to offer any significant benefits to employees who continued to work in the electricity sector.

Percebois and Wright [Percebois and Wright, 2001] compared the price performances of the French and the United Kingdom's (UK) electricity industries between 1990 and 2000. The impact of liberalisation was minimal in France while the electricity industry in the UK was de-integrated, privatised and liberated by the end of 1990s. In 1990, the state-owned French electricity was performing better than the state-owned UK industry [Percebois and Wright, 2001]. In 2000, the French industry was still performing better than the privately-owned UK industry. However, it was found that the privately-owned UK industry is capable of achieving faster reductions in prices to close the gap between itself and the French.

As a result of deregulation in New Zealand, the small electricity system and large generation and transmission systems are combined. This has resulted in higher than usual spinning reserves for New Zealand [Alvey and Cheung, 2000]. Previously, generating units with small contribution from interruptible loads provided these reserves. With the introduction of the market, the number of interruptible loads offered to the market increased as there were high marginal prices paid for reserves [Alvey and Cheung, 2000]. In addition to maintaining a secure system, this process has led to an overall reduction in cost of procuring sufficient reserves [Alvey and Cheung, 2000].

Maki [Maki, 2002] studied the changes in consumer living standards in New Zealand during the period of deregulation. It was found that the effect of deregulation varies among income classes and the high income classes benefited the most. However, it was found that these classes do not consistently nor exclusively benefit from deregulation. A study by Evans *et al.* [Evans *et al.*, 1996] concluded that there was a substantial improvement in macroeconomic indicators including labour productivity, taming of inflation and current account balance. It was also concluded that the unemployment rate declined after the initial process of restructuring.

The introduction of an electricity market in Germany has allowed customers to switch easily among a number of suppliers [Brunekreeft, 2000]. The electricity market has also maintained low spot prices. Although the network charges are relatively high, end-user prices for both residential and industrial users have decreased substantially. Overall, it was concluded that the introduction of competition in the German electricity market at the generation and retail stages seemed to be working [Brunekreeft, 2000].

2.6 ELECTRICITY INTENSITY, DEREGULATION AND ELECTRICITY CONSUMPTION

In the previous sections, the issues of electricity intensity and deregulation have been discussed for a number of industrialised and developing countries. In this section, an attempt is made to discuss whether deregulation has had any effect on the pattern of electricity consumption in the past years using the electricity intensities that have been analysed. Deregulation is considered to be a major structural change that has occurred in many electricity industries around the world and that any effect which it would have on the patterns of electricity consumption may affect the performance of the electricity consumption forecasting models to be proposed.

As discussed, electricity deregulation began in New Zealand in 1987, the United States in 1992, the United Kingdom in 1990, Germany in 1999 and Brazil in 1995. At this stage there seems to be little or no competition in the electricity industries of the Maldives, China, Japan, France, India or Indonesia, although reforms are underway to allow competition in many of these countries.

In New Zealand, the electricity consumption per capita continued to grow along a similar pattern from 1987 as for the previous years, although the reduction in electricity consumption due to the draught of 1992 can be clearly observed. There are also no significant changes in the pattern of electricity intensity either. The continuous slight increase in intensity from 1980 to 1991 and the decrease in intensity after 1991 cannot be attributed as a direct result of deregulation in 1987.

In the United States, deregulation in some states has had no significant influence on the aggregate electricity consumption per capita of the whole country. The electricity consumption per capita continued to increase throughout the whole period. The electricity intensity decreased slightly over the years but roughly at the same rate as those for New Zealand. The decrease in electricity intensity in the United States is apparent over the whole period except the few years of the late 1980s. Therefore, it can be concluded that the deregulation in the United States had no significant effect on the annual aggregate electricity consumption pattern.

In the United Kingdom, the slight growth in electricity consumption per capita continued throughout the whole period. However, the electricity intensity was slightly higher following the first two years of deregulation but continued to decrease along the usual pattern. Therefore, any direct effect on electricity consumption patterns due to deregulation is not apparent. Even in the case of Brazil, there seems to be no significant influence of deregulation in 1995 on electricity consumption patterns.

In the case of Germany the electricity consumption pattern has slightly increased after 1999, however the electricity intensity remained relatively unchanged. As deregulation was introduced only in 1999 and data here is available until 2002, it cannot be concluded at this stage that this is a direct effect of deregulation in Germany.

In addition, studies regarding deregulation of the electricity intensity, including many of those that have been referred to in this chapter do not include discussing their effect on electricity consumption patterns. Not a single research paper that discusses the direct effect of deregulation on electricity consumption patterns has been found at this stage. This is an indication that the level of electricity consumption is not an issue with regard to deregulation.

Overall, in countries where deregulation has been introduced, there seems to be no significant effect on the pattern of electricity consumption per capita or the electricity intensity. These patterns continue along the path of business as usual as far as the total electricity consumptions of the countries are concerned. Thus it can be concluded that the performance of the electricity forecasting models developed should not be affected as a result of deregulation.

Although not significantly apparent at the aggregate level, there may be some significant changes at the disaggregated levels for these countries, as some researchers believe that electricity intensity comparisons at aggregate levels may sometimes be misleading [Nagata, 1997] [Theriault and Sahi, 1997]. Unfortunately, data is not available to undertake analysis at this disaggregated level and therefore is not within the scope of this study.

2.7 SUMMARY

In this chapter, electricity per capita, GDP per capita, electricity intensity, electricity intensity curves and electricity intensity factors for selected countries and regions of the world have been obtained and analysed to examine any relationship that may exist between electricity consumption and the economic growth of a country or region. The link between economic growth and energy demand are strongly influenced by the stage of the development and the standard of living in a given region. It was found that the link between economic growth and electricity consumption is stronger in the developing countries than those for the industrialised countries. In the developing countries, the economies grow as more new industries that generally contribute to the economic wealth emerge. In the industrialised countries, although the electricity consumption remains high, electricity use is more stable or slow changing. In addition, the chances for increased efficiency, due to replacement of old equipment with modern equipment, in the industrialised countries are higher than those for the developing countries. This has contributed to a reduction in the electricity intensity of the industrialised countries. A general trend of a decreasing intensity in the industrialised countries and increasing intensity in the developing countries has also been observed. Although the level of the relationship may be different from country to country, this study has shown that economic growth and electricity consumption are related in all countries and regions of the world justifying the use of GDP and population in the Combined and VAL models to be proposed.

The chapter has also discussed the issue of deregulation in the electricity industry with specific regard to the factors contributing to deregulation and the impacts it has had on different electricity industries. Finally, the chapter discussed whether the introduction of deregulation has affected the patterns of electricity consumption. Using aggregate electricity consumption data for the countries analysed, it was found that there has been no significant impact on electricity consumption due to deregulation of the electricity industries. Therefore, it can be concluded that the performance of the electricity forecasting models to be proposed should not be affected by the introduction of deregulation.

Chapter 3

STATISTICAL TESTS FOR FORECASTING MODELS

3.1 INTRODUCTION

A model that is not statistically validated against the historical data cannot be accepted for forecasting. This chapter summarises the theory of the statistical tests that are used to check the validity of the various models that will be proposed in Chapter 4.

3.2 AUTOCORRELATION ANALYSIS

When applying a projection technique to a time series analysis, it is assumed that the data values are related to each other at one or more time periods apart. The extent of the relationship can be measured by taking two data sequences from the time series, one lagging the other by one or more time periods, and calculating the correlation coefficient between the two sequences. This calculation is often called correlation or autocorrelation.

The autocorrelation coefficients range from 0 to 1. When the correlation coefficients are high, i.e. close to 1, it implies that the data points are closely correlated at a certain time period. This means that it is statistically significant to make a forecast to the next time period based on the present data.

For a time series with n data points, a commonly used formula to calculate the autocorrelation coefficient (r_k) between data k periods apart is

$$r_k = \frac{\sum_{t=1}^{n-k}(Y_t - \overline{Y})(Y_{t+k} - \overline{Y})}{\sum_{t=1}^{n}(Y_t - \overline{Y})^2} \tag{3.1}$$

where,

Y_t is the data for the t^{th} observation and

$\overline{Y}$ is the average value of the time series.

This method was used to investigate the data series prior to the application of the Logistic model [Tay, 1985].

3.3 COEFFICIENT OF DETERMINATION

The coefficient of determination, r^2, is used to determine the effectiveness of using some independent variables to forecast a certain dependent variable. It should be noted that the coefficient of determination is a necessary but not a sufficient condition to forecast future values of the dependent variable [Porter *et al.*, 1991]. The coefficient of determination indicates the fraction of the total variance in the dependent variable that is explained by the model. It is defined as

$$r^2 = \frac{\sum(\hat{Y}_i - \overline{Y})^2}{\sum(Y_i - \overline{Y})^2} \tag{3.2}$$

where,

$\hat{Y}$ is the estimated value of Y

In simple regression the square root of the coefficient of determination is equal to the simple correlation coefficient.

Adding unimportant variables in a model will increase the value of the coefficient of determination to some extent [Bowerman and O'Connell, 1993]. Therefore, the *adjusted coefficient of determination* is often used, since it corrects for this increase by adjusting the coefficient of determination appropriately. This is defined as [Bowerman and O'Connell, 1993]

$$\bar{r}^2 = \left(r^2 - \frac{k-1}{n-1}\right)\left(\frac{n-1}{n-k}\right) \tag{3.3}$$

where,

k is the number of variables in the model, and

n is the number of data points used.

3.4 F-TEST

The F-test is a statistical test used to determine the adequacy of the model fit. This is the same as testing whether all the coefficients of the regression equation are zero. It is defined as

$$F = \frac{\sum(\hat{Y}_i - \bar{Y})^2 / (k-1)}{\sum(Y_i - \hat{Y}_i)^2 / (n-k)} \tag{3.4}$$

where,

k is the number of variables ($k = 2$ for simple regression).

The value of F, computed for a particular data set must be compared with the appropriate entry in a statistical table of F-test values (usually called the *critical value* of F corresponding to a particular probability level) to determine its significance for a given confidence level. The critical F values can be found in [Makridakis *et al.*, 1998]. These values are usually available in most statistical software. If the calculated value of F is greater than the critical value of F then it is concluded that the relationship between the independent variables, say X_1 to X_n, and the dependent variable Y is statistically significant and thus is not the result of chance.

3.5 T-TEST

The *t*-test is performed to assess the probability with which the forecaster can reject the hypothesis that a particular coefficient b' of a proposed model is different from zero [Makridakis *et al.*, 1998]. It is defined as

$$t = \frac{b'}{\sqrt{s_e^2 / \sum (x_i)^2}} \tag{3.5}$$

where, x is the deviation from the mean and s_e^2 is the standard error defined as

$$s_e^2 = \frac{\sum (Y_i - \hat{Y}_i)^2}{n-k} \tag{3.6}$$

When the value of t is calculated for the data, it is compared with a particular critical value of t (for a particular percentage probability of error) chosen from a standard t-distribution table [Makridakis *et al.*, 1998]. This can also be obtained from most software as well. If the critical value of t is less than the calculated value, the hypothesis that b' is zero can be rejected, with less than the percentage probability of error.

3.6 DURBIN-WATSON STATISTIC

Durbin-Watson (DW) statistic is often used in checking for independence of residuals produced by a particular model. It is defined as

$$DW = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2} \tag{3.7}$$

where e_t is the error at time t.

The numerator of the DW statistic calculates the difference between successive errors, squares these differences and adds them up. The denominator represents the sum of the squared errors. The DW statistic generally ranges from 0 through to 4, with an intermediate value of 2. More details on the theory behind the statistics can be found in [Makridakis *et al.*, 1998]. For random errors, the statistic is near 2. A value less than 2 indicates positive autocorrelation at lag one while a value more than 2 indicates negative autocorrelation at lag one. If there is autocorrelation at lag 1, then there is often correlation at other lags too [Makridakis *et al.*, 1998].

3.7 AUTOCORRELATION AND PARTIAL AUTOCORRELATION PLOTS

As discussed before, the autocorrelation as described in Section 3.2 is used when applying the Logistic model to a time series. When applying the autoregressive integrated moving average (ARIMA) technique to a time series, the series is initially observed for stationarity. Thus the autocorrelation plot, as defined by Equation 3.1, is readily used in determining whether a series is stationary or not. This is commonly referred to as the *autocorrelation function* (ACF). For stationary series the autocorrelation data drops to zero quickly as the time lags increase, while for non-stationary series they are significantly different from zero for several time lags.

In addition, a *partial autocorrelation function* (PACF) is used to measure the degree of association between Y_t and Y_{t-k}, of a time series represented by Y when the effects of other time lags – 1, 2, 3, …, k-1 – are removed. [Makridakis *et al.*, 1998]. The partial autocorrelation coefficient, r_{kk}, is defined as [Bowerman and O'Connell, 1993]

$$r_{kk} = r_1 \qquad \text{if } k = 1$$

$$r_{kk} = \frac{r_k - \sum_{j=1}^{k-1} r_{k-1,j} r_{k-j}}{1 - \sum_{j=1}^{k-1} r_{k-1,j} r_j} \qquad \text{if } k = 2,3, \ldots \tag{3.8}$$

where,

$r_{kj} = r_{k-1,j} - r_{kk} r_{k-1,k-j}$ for j = 1, 2, …., k-1 and

r_k is the autocorrelation coefficient at lag k

A *white noise* model is an example of a stationary time series. The autocorrelation coefficients of white noise data have a sampling distribution data that can be approximated by a normal curve with zero mean and standard error $1/\sqrt{n}$ where n is the number of observations in the time series [Anderson, 1942] [Bartlet, 1946] [Quenouille, 1949]. Quenouille [Quenouille, 1949] showed that if the time series is white noise, then the estimated partial autocorrelations are approximately independent and normally distributed with a standard deviation of $1/\sqrt{n}$. As the mean is zero and the standard error is $1/\sqrt{n}$ for white noise, it is expected that 95% of all sample ACF and PACF coefficients are within $\pm 1.96/\sqrt{n}$. Hence, the limit of $\pm 1.96/\sqrt{n}$ is used in ACF and PACF plots to assess if the data is white noise.

The ACF and PACF plots are not only used for analysing whether the series is stationary or not, but also in analysing whether the residuals produced by the ARIMA models are stationary as well.

3.8 PORTMANTEAU TESTS

The *Portmanteau tests* are another way of testing whether the residuals produced by a model are stationary or not. These tests check whether the set of residuals are significantly different from zero. One common test is the Box-Pierce test based on the Box-Pierce Q statistic [Box and Pierce, 1970]. It is defined as

$$Q = n\sum_{k=1}^{h} r_k^2 \tag{3.9}$$

where,

n is the number of observations in the series

h is the maximum lag being considered (usually h =20)

r is the autocorrelation coefficients.

Another common test is the Ljung-Box test [Ljung and Box, 1978]. It is defined as

$$Q^* = n(n+2)\sum_{k=1}^{h} (n-k)^{-1} r_k^2 \tag{3.10}$$

If the residuals are white noise, then the Q or Q^* statistic has a chi-square (χ^2) distribution with (h-m) degrees of freedom, where m is the number of parameters in the model that has been fitted to the data. The value of Q or Q^* obtained can be compared with the corresponding value in a standard chi-square table [Makridakis *et al.*, 1998] to assess if it is significant. If the value of Q or Q^* lies in the extreme 5% of the right-hand tail of the chi-square distribution, it can be concluded that the residuals are white noise.

3.9 ACCURACY MEASURES

When a model or a number of models are fitted to a particular data set, the models are often compared on the basis of how well the models fit the historical data and how well the models estimate the future consumption values. The first is generally referred in this thesis as *goodness of fit* or *fit*. The second is referred to as *forecasting accuracy*. When a model is fitted and goodness of fit is estimated it makes use of all available data. However, in measuring the forecasting accuracy for a particular time period, some actual data are discarded and held out while developing the models. The forecasts obtained by the developed models are then compared with the actual data that are held out to measure the forecasting accuracy. Therefore, forecasting accuracy gives a better measure of the performance of the model than the goodness of fit as a better model fit does not necessarily imply good forecasting [Makridakis *et al.*, 1998].

Two methods are used to measure the goodness of fit and forecasting accuracy throughout the thesis. They are *sum of the squared residuals* (SSR) and *mean absolute percentage error* (MAPE). The SSR is defined as

$$SSR = \sum_{t=1}^{n} (\hat{Y}_t - Y_t)^2 \tag{3.11}$$

and MAPE is defined as

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \left(\frac{Y_t - \hat{Y}_t}{Y_t} \times 100 \right) \right| \tag{3.12}$$

where,

Y_t is the actual consumption data,

$\hat{Y}_t$ is the corresponding predicted data, and

n is the number of data points used.

When SSR is averaged as for MAPE, it is commonly known as *mean square error* (MSE). MAPE is more often used in the thesis. SSR or MSE is mainly obtained from time to time for comparison purposes as this measure was used in the previous research involving the Logistic model [Tay, 1985].

3.10 SUMMARY

This chapter has introduced the various statistical tests that will be used in analysing the electricity consumption forecasting models to be proposed. A brief overview of the theory behind the statistics and their applications were also explained.

Chapter 4

ELECTRICITY FORECASTING MODELS

4.1 INTRODUCTION

In this chapter the proposed electricity forecasting models are described. The chapter first describes the Logistic model based on the logistic growth curve. Theory of the proposed econometric models is then described. Two forms of the econometric models are introduced. They are simple linear regression models and multiple linear regression models. Thirdly, the autoregressive integrated moving average (ARIMA) models are introduced and described. The fourth and fifth models proposed are based on the growth curves and are known as Harvey Logistic and Harvey models. Finally, the economic and demographic variables used in the economic models are applied in the original Logistic model to propose a Variable Asymptote Logistic (VAL) model. The VAL model also makes use of the ARIMA technique to forecast the independent variables.

4.2 THE LOGISTIC MODEL

4.2.1 Background

Over the years, growth and diffusion phenomena have been investigated by researchers in many disciplines, such as biology, demography, economy and agriculture. The term growth is commonly used in population studies, biology or chemistry while diffusion is commonly used in the technological and marketing studies [Carrillo and Gonzalez, 2002]. Growth curves have been used as a tool in all such studies where the process eventually approaches a saturation level.

Growth curves have been used frequently in technological forecasting [Kim *et al.*, 2003] [Masini and Frankl, 2003] [Franses, 2002] [Martino, 2003]. Twiss [Twiss, 1992] states that examination of a large number of past technologies indicates that it has not been random and that when a graph of performance, measured by a technological parameter, is plotted against time, an S-curve (or logistic) is obtained. It is assumed that a newer technology will exhibit the same behaviour. Therefore, the data for a partly established curve can be assumed to grow along an S-curve which can be fitted to the data from its emergence to the present day and extrapolated into the future.

A wide variety of growth curve models may be found in general and specific literature. Of these, the Logistic model is the most studied in practice [Carrillo and Gonzalez, 2002]. Bass [Bass, 1969] developed a growth model for the timing of initial purchase of new products. The Bass model is a combination of the Logistic and modified exponential models and therefore is widely used in technological innovations marketing [Jain and Rao, 1994] [Bhargava *et al.*, 1991].

As the Logistic model is widely studied, extensions and other forms of improved Logistic models are often found in the literature. Bewley and Fiebig [Bewley and Fiebig, 1988] developed a four parameter generalisation of the logistic growth curve, the flexible-logistic (FLOG) model, and applied it to telecommunications data. Meyer and Ausubel [Meyer and Ausubel, 1999] introduced a logistic model that allows for a sigmoidally increasing carrying capacity. Bewley and Griffiths [Bewley and Griffiths, 2003] compared the forecasting ability of 12 models on the market penetration of CDs and found that the flexible logistic model FLOG [Bewley and Fiebig, 1988] gave the best forecasts. On the other hand, Meade and Islam [Meade and Islam, 1995] compared the forecasting performance of a wide range of growth curve models. It was shown that the local logistic, simple logistic and the Gompertz models outperformed the more complex models such as the extended logistic and FLOG models. Frank [Frank, 2003] studied the diffusion of wireless communications in Finland where the Logistic model was fitted into the data using non-linear least squares. Forecasts made using this model were very accurate.

Over the years, a number of growth curve models have been proposed and applied to electricity forecasting [Giovanis and Skiadas, 1999] [Tay, 1985] [Bodger and Tay, 1987] [Skiadas *et al.*, 1993] [Sharp and Price, 1990] [Young, 1993] [Tingyan, 1990]. Giovanis and Skiadas [Giovanis and Skiadas, 1999] proposed a stochastic innovation diffusion model derived from the original logistic growth model and applied to the electricity consumption in Greece and United States. The model showed sufficiently good results for the applied data. The Logistic model has also been applied to the electricity consumption of New Zealand [Tay, 1985] [Bodger and Tay, 1987]. A modified form of the Logistic model has also been applied to the Greek electric system [Skiadas *et al.*, 1993]. While it is hard to conclude which model predicts electricity consumption most accurately, the various classes of logistic models have proved to be very effective in forecasting many social and technological patterns.

Apart from the application of the Logistic model to the electricity consumption in previous research conducted at this university [Tay, 1985] [[Bodger and Tay, 1987], there has been no direct application of the original form of the Logistic model for forecasting electricity consumption. The Logistic model that was applied to New Zealand at that time proved to be very effective in forecasting electricity consumption. Therefore, the Logistic model is initially revisited here to redevelop and update it with the recent available data. This will also give the opportunity to compare the historical forecasts made by the Logistic model and the national forecasts available at that time with the actual data that have been accrued since then. At this point it is important to clarify why the Logistic model has not been applied to consumption per capita as the per capita it is believed to represent more of S-curve type behaviour than the actual electricity consumption. Firstly, study of the application of the Logistic model to the consumption per capita has not shown any significant improvements. Secondly, if the Logistic model is applied to the consumption per capita in this study, the comparison among the different models become difficult as the other models will be applied directly to gross electricity consumption.

4.2.2 The Logistic Growth Curve

The Logistic growth curve assumes that there is an upper limit or asymptotic value to the energy consumption growth curve, which takes the general shape of a right skewed S-curve. The data value concerned increases slowly at the beginning and reaches a maximum rate of growth at a point of inflexion. From this point onwards, the rate of growth gradually decreases until the curve approaches the asymptote, referred to as the saturation level. There have been a number of applications of the Logistic growth curves including biological, technological and economic fields. It was concluded that the models presented by Pearl [Pearl, 1924], Fisher and Pry [Fisher and Pry, 1971] and Mansfield [Mansfield, 1961] are of relevance to electricity consumption modelling [Tay, 1985].

4.2.2.1 Pearl's Biological Growth Curve

There are five factors that must be taken into account in mathematically modelling the population growth of biological species [Pearl, 1924]. They are

1. the finite limit of land area of habitation;
2. the upper limiting asymptote of population constrained by (1);
3. the lower limiting asymptote of the population (= 0);
4. the epochal or cyclic character of growth, successive cycles being additive; and
5. the general S-shape of the growth curve.

In order to satisfy the five constraints, Pearl [Pearl, 1924] proposed the following general form of the logistic equation:

$$y = \frac{k}{1 + M \exp(F(x))} \tag{4.1}$$

where,

$F(x) = a_1x + a_2x^2 + a_3x^3 + ... + a_nx^n$,

M is a positive constant, and

k is the upper asymptote.

A third order equation of *F(x)* has been generally used with the assumption that less than five arbitrary constants are used in any practical problem.

4.2.2.2 A Technological Substitution Model

Fisher and Pry [Fisher and Pry, 1971] proposed the technological substitution model with the view that the human species has a few broad basic necessities which need to be satisfied such as food, clothing, shelter, health, education, transportation, communication, etc. Therefore, technological evolution consists mainly of substituting a new form of satisfaction for the old one.

The substitution model was based on three assumptions.

1. Many technological advances can be considered as the competitive substitution of one method of satisfying a need for another.
2. If a substitution has progressed as far as a few percent, it will proceed to completion; and
3. The rate of fractional substitution of a new technology for an old one is proportional to the remaining amount of the old one left to be substituted.

The equation for the substitution model is [Tay, 1985]

$$f = \frac{1}{1 + A\exp(-Bt)} \tag{4.2}$$

where,

$A = \exp(2ct_0)$

$B = 2c$

c is the half annual fractional growth in the early years

t_0 is the time at which $f = ½$.

This model is a specific case of the Pearl Curve (Equation 4.1) with the second and third order terms omitted and k set to 1.

4.2.2.3 Modelling the Rate of Imitation

Mansfield [Mansfield, 1961] examined the pattern or rate at which different firms follow an innovation. This helped in building a model for the rate of imitation. Tay [Tay, 1985] states that his approach and assumptions were different from those of Pearl and Fisher & Pry, but the final form of his model is a logistic growth curve.

The final form of his model is given by

$$M_t = \frac{n}{1+\exp[-(h+qt)]} \tag{4.3}$$

where,

n is the total number of firms which could possibly introduce an innovator,
M_t is the total number of firms which have done so at time t, and
h and q are constants.

4.2.2.4 The Logistic Model

Modelling of annual electricity consumption using the logistic growth curve based on the background and assumptions made by the three models described in sections 4.2.2.1 to 4.2.2.3 are of relevance to the electricity consumption trend in New Zealand [Tay, 1985]. In this research, it is assumed that these assumptions are relevant to any electricity consumption data.

The proposed Logistic model is

$$f = \frac{F}{1 + \exp(C_0 + C_1 t)} \tag{4.4}$$

where

F is the asymptotic value,

f is the annual electricity consumption data,

t is time in years, and

C_0 and C_1 are constants to be found using historical data.

The curve is fitted to the historical data by regression analysis using a linear form of the equation.

$$\ln\left(\frac{f}{F - f}\right) = C_0 + C_1 t \tag{4.5}$$

Future values of the electricity consumption were then calculated by extrapolating Equation 4.4. However, it should be noted that the following conditions apply when using the Logistic model to forecast electricity consumption [Tay, 1985].

1. The extrapolated portion of the curve should never be used to assess the adequacy of the curves to describe the historical growth.
2. No fundamentally new factors or forces influencing the rate of growth different from those which have operated during the known historical period of the consumption growth shall come into play in the extrapolated region, and
3. The value of the asymptote should be revised whenever additional data is available as its determination is subject to probable error.

4.2.3 Logistic Curve Fitting Technique

4.2.3.1 Estimating the Upper Limit

Consider the Logistic equation rewritten as

$$f = \frac{F}{1 + A\exp(a_0 + a_1 t)} \tag{4.6}$$

where,

F is the asymptotic value,

A is a positive constant,

f is the annual consumption data,

t is time in year, and

a_0 and a_1 are constants.

Fitting the Logistic curve is very much dependent on the asymptote F obtained. In this research F is obtained by regression analysis of the electricity consumption data concerned. This method should only be applied if the growth of development is at the latter stages [Tay, 1985]. The early development is strongly influenced by problems associated with immature technologies, such as inefficient theoretical understanding, lack of adequate materials, etc. and should not be used to predict the maturity of a technology.

If the upper limit F is underestimated, then the fitted curve rises too steeply and reaches its mid-point too early. Growth in the early years is overestimated but the forecast will begin to underestimate actual growth after the growth has reached about two-thirds of the estimated upper limit [Tay, 1985]. Using these arguments, it was suggested by Tay [Tay, 1985] that if the growth pattern has gone beyond the early stages of development, the goodness of the fit of the curve to the historical data can be used to estimate the optimal asymptote F. A Fibonacci search technique [Boas, 1963] was used to obtain the optimal asymptotes for the Logistic curves that were fitted to the consumption data in the various sectors.

4.2.3.2 *Fibonacci Search Technique*

Boas [Boas, 1963] has shown that the Fibonacci search technique is the most efficient search routine which involves only one variable and where the assumption of unimodality holds. While locating the optimal asymptote by this method, the sum of the squared residuals (SSR) is minimised between the fitted curve and the actual data. The Fibonacci search technique involves the use of Fibonacci numbers. These numbers are generated by the expression

$$z_n = z_{n-1} + z_{n-2} \qquad \text{for } n>2 \qquad (4.7)$$

with $z_0 = 1$ and $z_1 = 1$.

The first 21 Fibonacci numbers generated using this method is given in Table 4.1. The ratios of any two adjacent Fibonacci numbers tend to a constant value of 1.618, which has an inverse of 0.618 and is a ratio found in the aesthetics of fine art, architecture and natural construction.

Table 4.1 First 21 Fibonacci Numbers

No. of Experiments, N	Fibonacci No.	No. of Experiments, N	Fibonacci No.
0	1	11	144
1	1	12	233
2	2	13	377
3	3	14	610
4	5	15	987
5	8	16	1597
6	13	17	2584
7	21	18	4181
8	34	19	6765
9	55	20	10946
10	89		

Graphical representation of the Fibonacci search technique is illustrated in Figure 4.1. The Fibonacci search technique developed involves the following steps [Tay, 1985].

i) A range of values of F between which the optimal asymptote would lie is established. The lower limit, F_L, is taken as the maximum value of the known historical data and the upper limit, F_U, is taken as 100 times F_L. If no solution of F is found between these described ranges it is concluded that the historical data is little influenced by the asymptote and the problems of early development, as described in Section 4.2.4.1, dominate.

ii) Two equidistant points F_1 and F_2 from each end of the interval is established, as shown in Figure 4.1.

$$F_1 = F_L + d_1 \tag{4.8}$$

$$F_2 = F_U - d_1 \tag{4.9}$$

The distance d_1 is defined as

$$d_1 = \frac{z_{n-2}}{z_n} \times L \tag{4.10}$$

where,

z_{n-2} is the $(n - 2)^{\text{th}}$ Fibonacci number,

z_n is the n^{th} Fibonacci number,

$L = F_U - F_L$, and

n is the number of calculations to be performed.

Two calculations of SSR are made at the points F_1 and F_2, namely SSR_1 and SSR_2 respectively.

iii) A new interval F_L' and F_U' is established based on the relative magnitudes of the SSR_1 and SSR_2 that have been calculated in the previous step. If $SSR_1 < SSR_2$, then the region F_2 and F_U is discarded and the new upper limit is chosen as $F_U' = F_2$ and $F_L' = F_L$. Alternately if $SSR_1 > SSR_2$, then the lower region is discarded such that $F_L' = F_1$ and $F_U' = F_U$. This narrows the interval in which the optimal asymptote would lie based on the minimum SSR.

iv) The new value of the narrowed interval L' and a new value for the distance d_2, is then calculated as follows.

$$L' = F_U' - F_L' \tag{4.11}$$

$$d_2 = \frac{z_{n-3}}{z_{n-1}} \times L' \tag{4.12}$$

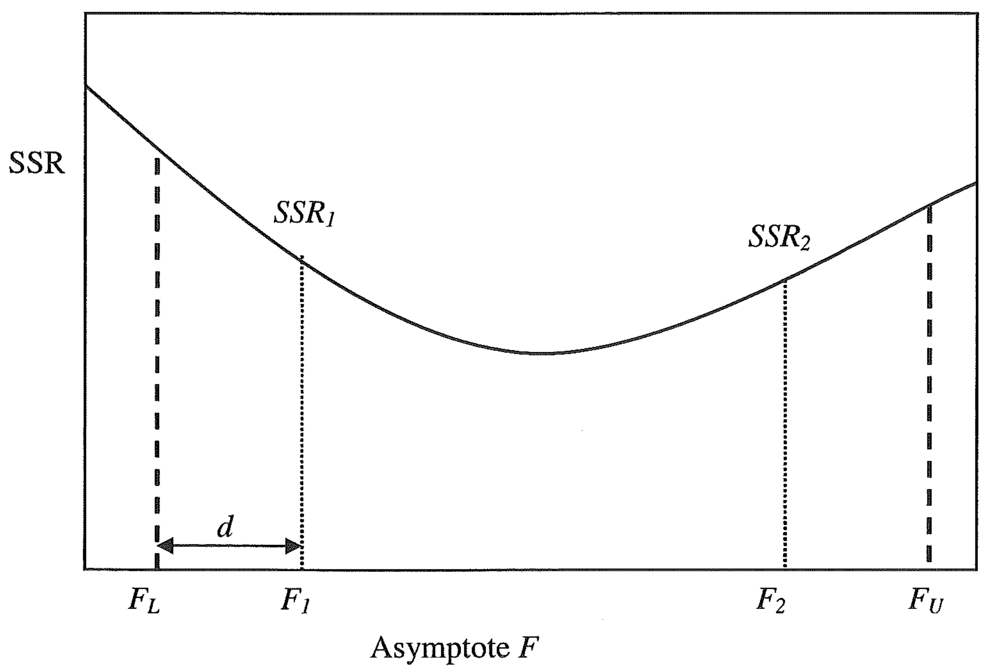

Figure 4.1 Minimising SSR in the Fibonacci search technique

v) Steps iii) and iv) are repeated, replacing old values of d and L with new values each time, until all the n iterations are performed.

At the final iteration F_1 and F_2 will be very close together as the interval L is narrowed significantly by the Fibonacci search technique at each step. At this point the optimal asymptote is chosen as the point with the lowest SSR.

4.3 ECONOMETRIC MODELS

4.3.1 Background

In econometric modelling the relationship between economic and demographic variables, and electricity consumption are used in developing forecasting models. There are a number of electricity forecasting models based on economic, social, geographic and demographic factors [Egelioglu *et al.*, 2001] [Harris and Liu, 1993] [Yan, 1998] [Rajan and Jain, 1999] [Fung and Tummala, 1993] [Liu *et al.*, 1991] [Lakhani and Bumb, 1978]. Egelioglu *et al.* [Egelioglu *et al.*, 2001] studied the influence of economic variables on the annual electricity consumption in Northern Cyprus using multiple linear regression analysis. It was found that the number of customers, the price of electricity and the number of tourists correlate with annual electricity consumption. Harris and Liu [Harris and Liu, 1993] found that price plays a major role in explaining conservation behaviour by electricity consumers. Yan [Yan, 1998] modelled residential electricity consumption using climatic variables for Hong Kong. Rajan and Jain [Rajan and Jain, 1999] expressed energy consumption patterns for Delhi as functions of weather and population. All these reflect that a model developed for one region may not be appropriate for another region. The variables affecting electricity consumption may vary from one region to the other. Fung and Tummala [Fung and Tummala, 1993] concluded that it was reasonable to use electricity price, gross domestic product (GDP), deflated domestic exports and population to forecast electricity consumption in Hong Kong. Liu *et al.* [Liu *et al.*, 1991] used gross domestic product, real electricity price and population in forecasting electricity consumption of Singapore. Lakhani and Bumb [Lakhani and Bumb, 1978] used residential price of electricity, per capita income and the estimated long run elasticity of demand in forecasting demand for electricity in Maryland.

In Chapter 2, it was shown that GDP and population are related to electricity consumption. Therefore in this section, linear regression models are proposed for electricity consumption based on GDP and population. In addition, the GDP and population data for most countries are more readily available than the other socio-economic data. The use of these two variables in all models for all countries and world regions will therefore allow an easy comparison of models. Where additional variables are used, the reasons for their use are explained in the relevant sections. The initial models are based on simple regression analysis. These models make use of the strength of the relationship between one of the independent variables and the electricity consumption pattern. Makridakis and Wheelwright [Makridakis and Wheelwright, 1989] state that either a simple model that may not completely duplicate reality or a complex model that is more accurate can be built, but this requires a large amount of effort and resources to be developed and manipulated. Even the most sophisticated model would have some part of reality that could not have been explained, since the number of factors in real life phenomena is infinite [Makridakis and Wheelwright, 1989].

4.3.2 The Regression Equation as a Forecasting Model

Linear regression is used as an essential tool to determine equations for straight line relationships. These equations can be used to extrapolate into the future. They can also be applied to non-linear relationships if those relationships can be mathematically transformed into linear forms. This procedure has already been used in the Logistic model to fit the growth curve for a given asymptote. In this section, two types of regression are used to propose electricity forecasting models. Simple linear regression (usually referred to as simple regression) is used in situations where it is assumed that a relationship exists between the dependent variable we want to forecast (electricity consumption) and another independent variable (example; GDP). Multiple linear regression (usually referred to as multiple regression) is used in situations where more than one independent variable (GDP, electricity price and population) is used to forecast electricity consumption.

4.3.2.1 Simple Regression as a Model

The proposed models using simple regression are of the form

$$Y = a + bX + u \tag{4.13}$$

where,

Y represents electricity consumption,

X can be GDP, price of electricity or population, and

u is the variations unexplained by the model or error term.

The values of a and b are obtained by linear regression usually using a statistical software package. In this research the software package MATLAB is used. In theory, the values of a and b are found by the following equations:

$$b = \frac{\sum XY/n - \overline{X} \times \overline{Y}}{\sum X^2/n - \overline{X}^2} \tag{4.14}$$

$$a = \overline{Y} - b\overline{X} \tag{4.15}$$

where,

$$\overline{Y} = \frac{\sum Y}{n}, \quad \overline{X} = \frac{\sum X}{n}, \quad \text{and} \tag{4.16}$$

n is the number of data points with which the regression is estimated.

The term u is added to the model to capture the fact that a part of the real process Y cannot be fully explained by the regression model. Usually the term u, which is often referred to as the *disturbance term* or *white noise*, is seldom needed for calculation or other practical purposes [Makridakis and Wheelwright, 1989]. However, the magnitude of the error will vary from model to model. For the regression model of Equation 4.13 to be statistically correct, u must have the following properties [Makridakis and Wheelwright, 1989] [Makridakis *et al.*, 1998].

1. The mean value of u must be equal to 0, as many factors that influence Y are not included in the regression equation.
2. The error term u must be a random variable. This basically means that the errors are to be independent of each other.
3. The disturbance term u must be normally distributed.
4. The variation of u must be constant.

In this research simple regression is not applied directly to the consumption data. Porter *et al.* [Porter *et al.*, 1991] state that knowledge of the past causal relationships often can be coupled with independent projections of related variables and used with regression analysis to develop a structural model that will provide an excellent forecast. In developing these electricity forecasting models, GDP, population and electricity price are used as independent variables along with the relevant consumption data to obtain the constant terms a and b.

Evaluating the Regression Model

Forecasting models are proposed for electricity consumption based on their dependence on either GDP or electricity price. Before applying such a model, the validity of the model can be ascertained by answering two questions [Porter *et al.*, 1991].

1. Is the model actually effective in explaining electricity consumption?
2. Can the hypothesis that the true value of constant terms a or b are equal to zero be rejected?

These questions can be answered by applying statistical tests. The first question is answered by applying an F-test while a t-test helps to answer the second [Porter *et al.*, 1991]. A necessary, but not sufficient, condition to forecast future values of Y is that the model be effective in explaining something about the dependent variable Y. This is done by calculating the coefficient of determination, r^2, which indicates the fraction of the total variance in the dependent variable that is explained by the model.

Causality and Regression

In simple regression it is assumed that one variable is dependent on another. Often, two variables may be related, although it is not appropriate to say that one variable depends on or is influenced by the value of the other [Makridakis and Wheelwright, 1989] [Makridakis *et al.*, 1998]. In such situations, the correlation between such two variables can be found. The correlation coefficient is a relative measure of the degree of relationship that may exist between two variables. The coefficient can vary from 0 (no correlation) to ± 1 (perfect correlation). Porter *et al.*[Porter *et al.*, 1991] states that thoughtful consideration must be given by forecasters to the statement, "*Correlation does not prove causation.*", the reason being that some correlations may be spurious and other correlations leave uncertainty as to the direction of causal influence. In other situations, correlation between two variables may reflect the influence of a third variable.

4.3.2.2 Multiple Linear Regression as a Model

The proposed multiple linear regression model to forecast electricity consumption using three independent variables is of the form:

$$Y = a + b_1 X_1 + b_2 X_2 + b_3 X_3 + u \qquad (4.17)$$

where,

Y is the electricity consumption,

X_1 is GDP,

X_2 is electricity price,

X_3 is the population, and

u is the error (as for simple regression).

The model can be generalised to n independent variables as

$$Y = a + b_1 X_1 + b_2 X_2 + b_3 X_3 \ldots\ldots + b_n X_n + u \qquad (4.18)$$

Multiple linear regression is an extension of the simple regression to accommodate more than one independent variable. Thus, the test for the coefficient of determination, the F-test and the t-test are applied in a similar manner as the simple regression to validate the models.

There are four basic assumptions that need to be accounted for each time multiple linear regression is used in practice [Makridakis and Wheelwright, 1989]. They are;

1. The dependent variable is linearly related to each of the independent variables.
2. There should be a constant variance of the regression errors. This assumption states that the forecasting errors must be constant over the entire range of observations. This is often referred to as *homoscedasticity.* If this condition is violated, the problem is called *heteroscedasticity.*
3. The regression residuals are independent of one another.
4. The residual values should be approximately normally distributed.

Each of these assumptions, except the assumption of independence of residuals, can be examined by producing appropriate plots of the residuals [Makridakis *et al.*, 1998]. These plots help to examine linearity and homoscedasticity assumptions. The residuals should not be related to the fitted values or the explanatory variables used in obtaining the model. Thus, each residual plot should show scatter in a horizontal band with no values too far from the band and no patterns such as curvature or increasing trend [Makridakis *et al.*, 1998]. For some models, Durbin-Watson statistics described in Chapter 3 are also used to study the independence of residuals produced by the regression models.

Multicollinearity is a practical concern in multiple linear regression models [Makridakis and Wheelwright, 1989]. This can be developed when two or more of the independent variables are highly correlated. When multicollinearity exists, it results in extremely large numbers that cannot be handled by the computer. However, it has been pointed out that multicollinearity is not a regression problem, but a computational problem [Makridakis *et al.*, 1998].

The multiple linear regression model will be referred to in this research as the *Combined model* or the *Combined Linear model.*

4.4 BOX JENKINS ARIMA MODELS

4.4.1 Background

Autoregressive Integrated Moving Average (ARIMA) models were popularised by George Box and Gwilym Jenkins in the early 1970s. The relevant information required to understand and study univariate time series ARIMA models was put together in a comprehensive manner by Box and Jenkins [Box and Jenkins, 1970] and later on by Box *et al.* [Box *et al.*, 1994]. Since then, a number of univariate ARIMA models have been published in the forecasting literature.

Box-Jenkins ARIMA models are well known in all areas of univariate time series forecasting. El-Bassiouni and El-Habashi [El-Bassiouni and El-Habashi, 1991] used Box-Jenkins methodology over econometric and regression techniques in forecasting compulsory motor insurance claims in Kuwait. Hsu and Liu [Hsu and Liu, 1991] developed an ARIMA transfer function model to evaluate the interactions between energy use and particulate air pollution in eight major cities in Taiwan. Preez and Witt [Preez and Witt, 2002] applied univariate and multivariate ARIMA and state space models to forecast international tourism demand. The study revealed that in terms of univariate and multivariate prediction error, ARIMA modelling is clearly the best method. When all of their empirical results were taken into account, the moving average ARIMA models seem to be the best if a specific choice of forecasting model has to be made. Pflaumer [Pflaumer, 1992] used the Box-Jenkins approach for forecasting the population of the United States. He concluded that the Box-Jenkins method produced population forecasts that are at least as reliable as those done with more traditional demographic methods. Fildes and Lusk [Fildes and Lusk, 1984] conducted a survey of expert forecasters in both the UK and the US. The survey showed that for short horizons Box-Jenkins was the most accurate method and concluded that there was no evidence that Box-Jenkins performs worse for long horizons than short. Binroth *et al.* [Binroth *et al.*, 1979] applied the Box-Jenkins method, multiple linear regression analysis, and two new regression-based techniques, referred to as *minimum relative error regression analysis* and *dynamic regression analysis* to forecast rubber-commodity price-index data. It was found that the Box-Jenkins method and the minimum relative error regression technique gave the most accurate results. Pack [Pack, 1990] stated that ARIMA models are more readily expandable than simpler models to represent real world time series that contain interventions, calendar variations, outliers, variance changes and so on. He pointed out that ARIMA models should be given a chance to demonstrate their maximum potential in any empirical accuracy investigation. Ayeni and Pilat [Ayeni and Pilat, 1992] concluded that the ARIMA method performed better over the decline curve method in forecasting and estimating crude oil reserves. Cranage and Andrew [Cranage and Andrew, 1992] showed that the Box-Jenkins model performed better than an econometric model in forecasting restaurant sales.

ARIMA models have also been successfully used in forecasting electricity consumption. Abdel-Aal and Al-Garni [Abdel-Aal and Al-Garni, 1997] developed ARIMA models for forecasting domestic electric energy consumption in the Eastern Province of Saudi Arabia and compared these with regression and abductive network machine-learning models. The results showed that ARIMA models required less data, have fewer coefficients, and are more accurate. Chavez *et al.* [Chavez *et al.*, 1999] used ARIMA models for modelling and forecasting future energy production and consumption in Asturias (northern Spain). The models had a satisfactory degree of statistical validity and were suitable for use as reference inputs in a regional energetic plan. Saab *et al.* [Saab *et al.*, 2001] investigated different univariate-methodologies to model and forecast electricity consumption in Lebanon. The study concluded that an autoregressive model with a high pass filter gave the best forecasts for the energy data. Wong and Rad [Wong and Rad, 1998] used ARIMA models in forecasting yearly electricity consumption for Hong Kong. In power systems, ARIMA models have also been very successful in short term load forecasting [Gross and Galiana, 1987]] [Hagan and Behr, 1987] [Komprej and Zunko, 1991].

4.4.2 Forecasting Using ARIMA Models

The Box-Jenkins methodology for modelling time series consists of identification, estimation, testing and forecasting [Makridakis *et al.*, 1998] [Farnum and Stanton, 1989]. In the identification stage, the time series is analysed to assess whether it is stationary. If the series is not stationary, the series is differenced to make it stationary. Any required transformation of the data is also carried out at this stage. This process helps to identify potential models using the autocorrelation function (ACF) and partial autocorrelation function (PACF). For the potential models, the parameters of the models are estimated using either least squares or maximum likelihood. Within those models, the best model is chosen using suitable criteria. Diagnostic tests of the model are then carried out. If the model is accepted, then the model is used for forecasting.

4.4.2.1 *Analysis of Time Series for Stationarity*

A time series, Y, is *stationary* if the following conditions are satisfied for all values of time *t* in the time series [Harvey, 1993]:

$$E(Y_t) = \mu \tag{4.19}$$

$$E[(Y_t - \mu)^2] = \sigma_y^2 = \gamma(0) \tag{4.20}$$

and

$$E[(Y_t - \mu)(Y_{t-\tau} - \mu)] = \gamma(\tau) \quad , \tau = 1, 2, .. \tag{4.21}$$

where,

μ is the mean of the data,

σ^2 is the variance of the data, and

γ is the covariance of the data.

Equation 4.19 and 4.20 define the mean and variance of the data, while Equation 4.21 gives the autocovariance at lag τ. The mean, variance and autocovariance can be estimated from:

$$\hat{\mu} = \bar{Y} = \frac{1}{n}\sum_{t=1}^{n} Y_t \tag{4.22}$$

$$\hat{\gamma}(0) = \frac{1}{n}\sum_{t=1}^{n}(Y_t - \bar{Y})^2 \tag{4.23}$$

$$\hat{\gamma}(\tau) = \frac{1}{n}\sum_{t=\tau+1}^{n}(Y_t - \bar{Y})(Y_{t-\tau} - \bar{Y}) \qquad , \tau = 1, 2, .. \tag{4.24}$$

If a series is stationary, it means that there is no growth or decline in the data. Thus, a plot of the time series along the time axis will be roughly horizontal. A time series is *stationary in the mean* if there is no evidence of a change in the mean over time. A time series is *stationary in the variance* if there is no obvious change in the variance over time. Thus, a visual plot of the time series is often enough to convince that the data are stationary or non-stationary [Makridakis *et al.*, 1998]. However, in this research autocorrelation (ACF) and partial autocorrelation (PACF) plots are used to assess whether a series is stationary.

4.4.2.2 Differencing

Differencing is a method of removing non-stationary aspects of the time series. A differenced series, Y_t', represents the change between each observation in the original series.

$$Y_t' = Y_t - Y_{t-1} \tag{4.25}$$

Differencing reduces the number of data points from n to (n-1) as the first observation cannot be differenced. As for the original series, the differenced series can be examined for stationary. If the differenced data does not appear stationary, the data is differenced a second time to obtain Y_t''. Thus

$$Y_t'' = Y_t' - Y_{t-1}' = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) = Y_t - 2Y_{t-1} + Y_{t-2} \tag{4.26}$$

Usually it is not necessary to go beyond second-order differencing as real data generally involve non-stationarity of only the first or second level [Makridakis *et al.*, 1998].

Non-stationary seasonal data cannot be made stationary by just first and second differencing. For these data, *seasonal differencing* is applied. A seasonally differenced series, Y_t', is the change between observations separated by s time periods, where s is the number of seasons [Makridakis *et al.*, 1998]. Thus, for monthly data having an annual 12-month pattern, the seasonal difference is

$$Y_t' = Y_t - Y_{t-12} \tag{4.27}$$

If the data set does not appear stationary after the seasonal differencing, first and second differences are applied in a similar fashion to the seasonally differenced series.

Very often the back shift operator, *B*, is used to denote the differencing.

$$BY_t = Y_{t-1} \tag{4.28}$$

and

$$B(BY_t) = B^2 Y_t \tag{4.29}$$

In the case of seasonal differencing:

$$B^{12} Y_t = Y_{t-12} \tag{4.30}$$

Thus, Equation 4.26 can be written using the operator B as

$$\begin{aligned} Y_t'' &= Y_t' - Y_{t-1}' \\ &= Y_t - 2Y_{t-1} + Y_{t-2} \\ &= Y_t - 2BY_t + B^2 Y_t \\ &= (1 - 2B + B^2) Y_t \\ &= (1 - B^2) Y_t \end{aligned} \tag{4.31}$$

4.4.2.3 *Identifying ARIMA Models*

An *autoregressive* (AR) model of order p can be described by the equation [Makridakis *et al.*, 1998]:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + ... + \phi_p Y_{t-p} + e_t \tag{4.32}$$

This model is different from a standard order p regression equation, as in a regression equation the variables Y_{t-1}, Y_{t-2} ... Y_{t-p} represent different time series, while in this model the variables are time lagged values of the forecast variable and therefore named as *autoregression.*

A *moving average* (MA) model consists of the past errors as the explanatory variable. A moving average model of order q is described by

$$Y_t = c + \theta_1 e_{t-1} + \theta_2 e_{t-2} + ... + \theta_p e_{t-q} + e_t \tag{4.33}$$

where,

e_t are the error series.

Autoregressive (AR) models are coupled with the moving average (MA) models for stationary series to form autoregressive moving average (ARMA) models. For non-stationary series differencing is required and the models are therefore called autoregressive integrated moving average (ARIMA) models.

ARIMA models are generally written as ARIMA (p,d,q), where p represents the order of the autoregressive (AR) part, d denotes the degree of first differencing (I) involved and q denotes the order of the moving average (MA) part. Thus, a pure AR(p) model can also be written as ARIMA(p,0,0) while a pure MA(q) model can also be written as ARIMA(0,0,q)

Identifying a model is somewhat complicated. Often ACF and PACF provide some guidance on how to select pure AR or pure MA models. When there is no obvious pure AR or pure MA model then mixed ARMA models are considered. Often there may be more than one plausible model and a method for selecting the best models is needed. There are a number of model selection criteria including Akaike's Information Criterion (AIC) [Akaike, 1974], Bayesian Information Criterion (BIC) and Final Prediction Error (FPE) [Brockwell and Davis, 2002]. AIC is defined as [Brockwell and Davis, 2002]

$$AIC = -2\ln L + 2m \tag{4.34}$$

where

$m = p + q + 1$ and L is the likelihood of the estimated parameters (Introduced in the next section).

In situations where seasonal differencing is involved, the order of seasonal parts (P and Q) is also added to the value of m. This research uses a bias corrected version of AIC known as AICC, defined as [Brockwell and Davis, 2002]

$$AICC = 2\ln L + \frac{2(p+q+1)n}{(n-p-q-2)} \tag{4.35}$$

where, n is the number of data points used.

The selected model is the model with the lowest AICC value.

4.4.2.4 Parameter Estimation

When a tentative model is identified the parameters ϕ and θ need to be estimated accurately. The method of least squares can be used for ARIMA models involving only the AR component. However for models involving the MA component an iterative method has to be used.

The *maximum likelihood* is used in this research. This method finds the values of the parameters that maximise the likelihood *L*. This method is favoured by statisticians as it has some desirable statistical properties [Brockwell and Davis, 2002].

The Gaussian Likelihood for an ARMA process is given by [Brockwell and Davis, 2002]

$$L(\phi,\theta,\sigma^2) = \frac{1}{\sqrt{(2\pi\sigma^2)^n r_0 \ldots r_{n-1}}} \exp\left\{-\frac{1}{2\sigma^2}\sum_{j=1}^{n}\frac{(Y_j-\hat{Y}_j)^2}{r_{j-1}}\right\} \tag{4.36}$$

where,

$$E(Y_{n+1}-\hat{Y}_{n+1})^2 = \sigma^2 r_n \tag{4.37}$$

The maximum likelihood estimators $\hat{\phi}$, $\hat{\theta}$ and $\hat{\sigma}$ are obtained by partial differentiation of *ln* $L(\phi,\theta,\sigma^2)$ with respect to σ and noting that $\hat{X}_j$ and r_j are independent of σ^2. The maximum likelihood estimators $\hat{\phi}$, $\hat{\theta}$ and $\hat{\sigma}$ must satisfy the following equations [Brockwell and Davis, 2002]:

$$\hat{\sigma}^2 = \frac{1}{n} S(\hat{\phi},\hat{\theta}) \tag{4.38}$$

where,

$$S(\hat{\phi},\hat{\theta}) = \sum_{j=1}^{n}(Y_j-\hat{Y}_j)^2 / r_{j-1} \tag{4.39}$$

and $\hat{\phi}$, $\hat{\theta}$ are the values of ϕ, θ that minimise

$$\lambda(\phi,\theta) = \ln(n^{-1}S(\phi,\theta)) + n^{-1}\sum_{j=1}^{n}\ln r_{j-1} \tag{4.40}$$

This research makes use of the software ITSM2000 provided by Brockwell and Davis [Brockwell and Davis, 2002] to obtain these estimates. Initial values are first obtained for ϕ and θ. ITSM then systematically searches for the values of ϕ and θ that minimises the reduced likelihood (Equation 4.40) and computes the corresponding maximum likelihood estimate of σ^2 using Equation 4.38.

4.4.2.5 *Diagnostic Checking of Residuals*

Diagnostic checking is carried out to verify that the chosen model is adequate. This is done by studying the residuals to see if any patterns remain unaccounted for. For a good forecasting model, the residuals left over after fitting the models should represent white noise [Makridakis *et al.*, 1998] [Chatfield, 2000]. The residuals are analysed in a similar way as the time series itself. Thus, the ACF and PACF of the residuals for acceptable models should lie within the limits of $\pm 1.96/\sqrt{n}$ more than 95% of time. In addition these, models are tested using either of the *portmanteau tests* and compared against the chi-square distribution (See Chapter 3 for details).

Once an appropriate model has been fitted to the data, the fitted model is used to forecast electricity consumption.

4.5 HARVEY LOGISTIC AND HARVEY MODELS

4.5.1 Background

Logistic models proposed in Section 4.2 are attractive in situations where there is thought to be a saturation level to a time series. The Logistic model uses a Fibonacci search technique to locate the saturation level or asymptote F. In that model, the asymptote F needs to be estimated before the required parameters of the Logistic model may be estimated. This prior estimate of the saturation level has been a main factor that contributes to low forecasts by the Logistic model in some situations [Mohamed and Bodger, 2003]. Thus the search for another growth curve model whose saturation levels are not as much constrained by the Logistic model is continued.

A time series forecasting model based on the Logistic curve was proposed by Harvey [Harvey, 1993] [Harvey, 1984]. Mar-Molineo [Mar-Molineo, 1980] and Oliver [Oliver, 1981] applied a logistic curve to forecast the number of tractors in Spain. Young [Young, 1993] studied nine different growth curve models including the Logistic and Harvey models by comparing their forecasting accuracy. The comparison revealed that the Harvey model was one of the three proposed models for forecasting time series with an unknown upper limit. Therefore, two models for electricity consumption are developed based on the model proposed by Harvey [Harvey, 1993] [Harvey, 1984]. These models do not require a saturation level to be estimated prior to estimation of the parameters. However, the model approaches a saturation level with time. The first model is based on the general logistic models. Therefore, this model has been named in this research as the *Harvey Logistic* models, due to their similarity with the Logistic model. The second model is based on the general modified exponentials. It has been named as the *Harvey* model.

4.5.2 Harvey Logistic Model

Univariate time series models are often based on a local, rather than a global trend [Harvey, 1984]. In local trend models, the recent observations receive more weight when forecasting than those in the more distant past. In global trend models, the time path of the data concerned is regarded as following a deterministic function of time, upon which is added a disturbance or error term.

The electricity consumption, $f(t)$, can be represented by the Logistic function as

$$f(t) = \frac{\alpha}{1+\beta e^{\gamma t}} \qquad 1 \leq t \leq T \tag{4.41}$$

where,

α is the saturation level,

β and γ are parameters to be estimated, and

t is the time in years.

When the above model is differentiated with respect to t and natural logarithms taken on both sides, the following equation is obtained [Harvey, 1984]:

$$\ln\frac{df(t)}{dt} = 2\ln f(t) + \delta + \gamma t \tag{4.42}$$

where,

$$\delta = \ln\left(\frac{-\beta\gamma}{\alpha}\right)$$

Using the above, the proposed Harvey Logistic model is [Harvey, 1984]

$$\ln y_t = 2\ln Y_{t-1} + \delta + \gamma t + \varepsilon_t, \quad t = 2\ldots T \tag{4.43}$$

where,

Y_t is the electricity consumption at year t,

$y_t = Y_t - Y_{t-1}$, $\qquad t = 2\ldots T$,

ε_t is the disturbance term with zero mean and constant variance, and

δ and γ are constants to be found by regression.

Although Equation 4.43 contains a deterministic trend component, it is obviously a local trend model when viewed in terms of the electricity consumption, Y_t [Harvey, 1984]. This model will be referred hereafter as the Harvey Logistic model.

Equation 4.43 can be rearranged to give

$$\ln\left(\frac{y_t}{Y_{t-1}^2}\right) = \delta + \gamma t + \varepsilon_t \tag{4.44}$$

The parameters δ and γ are found by regressing $\ln\left(\frac{y_t}{Y_{t-1}^2}\right)$ on t. Equation 4.44 can be written as

$$y_t = Y_{t-1}^2 e^{(\delta+\gamma t)} \tag{4.45}$$

Since $y_t = Y_t - Y_{t-1}$, then

$$Y_t = Y_{t-1} + Y_{t-1}^2 e^{(\delta+\gamma t)} \tag{4.46}$$

The h-step ahead forecasts of the electricity consumption, $\hat{Y}$, can be made by using

$$\hat{Y}_{t+h} = \hat{Y}_{t+h-1} + \hat{Y}_{t+h-1}^2 e^{(\delta+\gamma(t+h))} \tag{4.47}$$

The forecast for electricity consumption takes the form of the Logistic curve and gradually approaches the saturation level α.

4.5.3 Harvey Model

The general modified exponential function is of the form [Harvey, 1984]:

$$f(t) = \alpha(1+\beta e^{\gamma t})^k \tag{4.48}$$

The value of k determines the form of the function $f(t)$. When k = -1, $f(t)$ is Logistic and when k = 1 it is a simple modified exponential.

Differentiating and taking the natural logarithm as for the Logistic model led to the following model [Harvey, 1984]:

$$\ln y_t = \rho \ln Y_{t-1} + \delta + \gamma t + \varepsilon_t \tag{4.49}$$

where,

$$\rho = \frac{k-1}{k},$$

$\delta = \ln\left(k\beta\alpha^{1/k}\gamma\right)$, and

ρ, β and γ are parameters to be estimated

Equation 4.49 will be referred to hereafter as the Harvey model.

Equation 4.47 can then be modified to make forecasts as follows:

$$\hat{Y}_{t+h} = \hat{Y}_{t+h-1} + \hat{Y}^{\rho}_{t+h-1} e^{(\delta+\gamma(t+h))} \qquad (4.50)$$

4.6 VARIABLE ASYMPTOTE LOGISTIC (VAL) MODEL

4.6.1 Background

Growth curve models like the Logistic are based on the S-shape curve that ultimately reaches a saturation level. Such growth curve models may be based on the normal distribution [Stapleton, 1978], Weibull function [Sharif and Islam, 1980], etc. In such models, the estimated saturation level is used as one of the fitted parameters of the growth functions. Leach [Leach, 1981] demonstrated that the prediction power of the logistic growth function can be improved by taking into account the systematic changes in the saturation level. The idea of varying saturation level can also be found elsewhere [Maharajan and Peterson, 1978] [Maharajan *et al.*, 1979] [Sharif and Ramanathan, 1981] [Sharif and Ramanathan, 1984]. Skiadas *et al.* [Skiadas *et al.*, 1993] showed that the forecasting ability of the logistic function for the Greek electric system is improved using the correlations of some socio-economic variables to describe the saturation level.

A Variable Asymptote Logistic (VAL) model is proposed that incorporates economic and demographic variables and uses the ARIMA technique to forecast the variables. The saturation level of the logistic curve is initially estimated by the Fibonacci search technique. Correlation of the estimated saturation level with population, price of electricity and gross domestic product (GDP) will be studied. Based on the correlation, the VAL model is proposed using one or more of the above explaining variables. The VAL model could be regarded as a mixture of the three different models that have been proposed so far. Multiple linear regression is used in studying the correlation between the explaining variables and electricity consumption. Since ARIMA techniques are well known for predicting economic variables, they are used in predicting future values of GDP, price of electricity and population.

4.6.2 Variable Asymptote Logistic Approach

4.6.2.1 Proposed Model

The Logistic model is described by

$$f = \frac{F}{1+\exp(a_0 + a_1 t)} \tag{4.51}$$

where,

F is the saturation level

f is the electricity consumption

a_0 and a_1 are constants

t is the time in years

In the VAL model, the saturation level F is estimated using the explaining variables ($X_1 \ldots X_n$) and used as a variable asymptote *F(X)* in Equation 4.51. Thus, the proposed VAL model takes the form

$$f = \frac{F(X_i)}{1+\exp(a_0 + a_1 t)} \tag{4.52}$$

$$F(X_i) = c_0 + \sum_{i=1}^{n}(c_i . X_i) \tag{4.53}$$

where,

$F(X_i)$ is the saturation level expressed as a function of n variables

c_0 and c_i are the parameters obtained from the explaining variables.

A modified logistic function based on the sigmoid logistic function has been proposed previously for the Greek electric system [Skiadas *et al.*, 1993]. However, the sigmoid logistic function is different from the Logistic model in terms of its description and the method used to obtain the saturation levels.

The main stages involved in the VAL model are:

1. Estimate the saturation level F using the Fibonacci search technique.
2. Correlate F with the explaining variables considered and re-estimate F using these variables.
3. If the re-estimated F does not explain the saturation level adequately, reconsider the explaining variables and repeat step 2.
4. Obtain forecasts of the explaining variables using ARIMA technique.
5. Estimate future saturation levels F using the forecasts of the explaining variables.
6. Use the variable F values in Equation 4.52 to forecast electricity consumption.

4.6.2.2 Estimation of Saturation Level

The Fibonacci search technique as applied for the original Logistic model is used to obtain sets of initial estimates for the saturation levels. For example, if electricity consumption data for a particular country is available from 1950 to 2002, then initial estimates of saturation levels may be obtained for the period 1980 to 2002. The saturation level for 1980 is obtained by using electricity consumption data from 1950 to 1980, and similarly the saturation level for 1981 is obtained by using data from 1950 to 1981. Thus, the saturation level for 2002 represents what has been obtained using data from 1950 to 2002. In this case, the saturation levels are obtained for the period 1980 to 2002.

The saturation levels obtained are then studied by plotting them against time. Uniformly increasing or nearly constant trends in the saturation levels are generally expected as this would indicate more mature electricity industries and would facilitate more successful application of the VAL model. Often large sudden changes, generally with overall decreasing trends, in the saturation levels represent immature electricity sectors and the application of the VAL model may not produce very convincing results. However, this does not necessarily mean that one should discard the application of such data. This is generally noted as a caution that the VAL model may not be very effective for immature data sets.

4.6.2.3 Re-estimation of the Saturation Level

The saturation levels obtained are correlated with the selected economic and demographic variables. These variables are generally a combination of GDP, population and price of electricity. Based on the strength of the correlation, an initial set of variables are selected to be used in re-estimating the saturation levels. The selected variables are used to obtain estimates of the saturation levels using multiple linear regression.

Statistical tests such as the Durbin-Watson statistic, coefficient of determination and *F*-test are used in evaluating the applicability of the re-estimated saturation levels using the explaining variables. If the re-estimated saturation levels are not adequately satisfied then the selected variables are reconsidered and this process is repeated until the statistical tests are satisfied. Sometimes, the choice of the period of the initial set of saturation levels (in this case 1980 to 2002) may need to be revised (say from 1984 to 2002) in order for the re-estimated saturation levels to be more adequately satisfied. In situations where possible, the best approach is to re-estimate the saturation level for various combinations of explaining variables and select the choice that would best satisfy the statistical tests.

When the explaining variables to be used in re-estimation are finalised, accurate forecasts of the variables are needed. ARIMA techniques are often used in these types of forecasting [Canarella and Pollard, 1989] [Ilkka Virtanen and Yli-Olli, 1987] [Pflaumer, 1992] [Binroth *et al.*, 1979]. Therefore, ARIMA methods are used in forecasting population, price of electricity, and GDP. The forecasts of these variables are employed in forecasting the saturation levels for electricity.

4.6.2.4 VAL Method and Forecasting

In the Logistic model, the asymptote F calculated for a particular data set is a constant for the forecast to be made. If a forecast is to be made by the Logistic model from the year 2002 onwards, the Fibonacci search technique is used to obtain a constant F, which is then used in Equation 4.51, as the time in years t is increased to obtain the forecasts.

In the VAL model, the asymptote F for each of the forecasted years is different from one another. Thus, in forecasting electricity consumption for 2003 the re-estimated F value of 2003 is used, while to obtain forecast for 2010 the re-estimated F value of 2010 is used. Therefore, as the name suggests a variable asymptote method is employed in the VAL model as compared with the constant asymptote of the Logistic model. Thus, this model allows more flexibility as the forecasts will not be as much constrained as the Logistic model and allows the use of economic and demographic variables to be used in a growth curve model to forecast electricity consumption.

In all cases, the forecasts by the VAL model will be compared with the original Logistic model for forecasting accuracy. This gives an indication whether the VAL model has performed better or worse than the Logistic model upon which the VAL model is based. The VAL model for a particular data set is only accepted if it has performed better than the Logistic model for the same data set.

4.7 SUMMARY

Six models for electricity forecasting have been proposed and described. Three of these models are based purely on growth curves. They are the Logistic model, the Harvey Logistic model and the Harvey model. The various transformations of econometric models including the Combined model have also been described. The autoregressive integrated moving average (ARIMA) models have also been proposed for electricity forecasting. Finally, the chapter proposes a Variable Asymptote Logistic (VAL) model that includes economic and demographic variables and uses the ARIMA technique in a Logistic model.

Of the proposed models, the ARIMA models and regression models have been more frequently applied in electricity forecasting. The Logistic model has been rarely applied in electricity forecasting. The Harvey Logistic model and Harvey model have not been previously applied to electricity forecasting. Although a modified Logistic model has been applied to electricity forecasting, the VAL model with a new transformation which has some similarity to the modified Logistic model is a completely new model proposed for electricity forecasting. The applications of the models to electricity consumption in the various countries and regions of the world will give a good idea of the performances of the models to electricity forecasting in general and will allow the comparisons of the models using different sizes of data that correspond to very different sizes of economy and demography.

Chapter 5

ELECTRICITY INDUSTRY IN NEW ZEALAND

5.1 INTRODUCTION

A social system, large or small, is reliant on energy. It is the single most important entity, which allows a society to function. At a national level, energy supply and demand, in all its forms, is a major issue, which can have important impacts on the way a government or large corporations financially invest. At a small level it may be that efficiency of supply is paramount. Either option can have significant impacts on the environment.

One form of energy supply and consumption that is readily measurable is electricity. The New Zealand electricity market has changed dramatically in the past. Therefore it is very useful to summarise these changes before any research on the current issues of the electricity industry is conducted. By studying the historical changes and current structure of the New Zealand electricity industry, an overview of the developments and the structures of the electricity industry in other countries can be appreciated. Although New Zealand electricity industry is smaller than those of the United States and the United Kingdom used in this research, a detailed study of the New Zealand electricity industry is presented here to give an overall idea to the reader on how the electricity industry in a country has been transformed from its beginning to its current stage. In addition, such an understanding will allow better explanations on the performances of the models to be proposed for New Zealand.

The electrical industry consists of generators, network owners, retailers, service providers, consultants and manufacturers. The aim of this chapter is to summarise the evolution and developments of the New Zealand electricity industry to show the myriad of events that have given rise to the whole. The chapter introduces some of the very early stages of electricity supply and continues with the various changes that occurred during the development stages with emphasis on the governing Rules and Acts of the electrical industry which have been introduced from time to time. The chapter concludes with a brief summary of the recent changes in the electrical industry. Sections 5.2 to 5.11 are summarised from Martin [Martin, 1998].

5.2 THE EARLY DAYS OF ELECTRICITY

The first recorded use of electricity in New Zealand was in 1861 for a private telegraph line between Dunedin and Port Chalmers. In 1863 the first government lines by provincial councils linked Christchurch to Lyttelton. Following that Invercargill was linked to Bluff in 1864. In 1865 the Electric Telegraphic Act established a central governmental monopoly over the transmission of messages, and provided for state construction, maintenance and regulation of telegraphic telecommunications.

The first substantial use of electricity in New Zealand was for lighting, like it was in many other countries. In April 1879, a jeweller's window in Wellington's Lambton Quay was lit. This was the time when electricity became a little more familiar to people. In the 1880's electricity was adopted by travelling circuses as 'Electric Circuses'. The famous Professor Bickerton of the Canterbury University gave a successful demonstration of the electric light. In the same year, the usage of electricity was developed to reach a commercial stage for the first time. In 1882, the Roslyn Mills factory in Dunedin was lit. This has been regarded as the first practical usage of electricity in New Zealand beyond demonstrations and displays. It was also claimed that a private a house in New Zealand was lit this year. This was the house of Moss Davis, 29 Princess St, Auckland. Also in 1880, Dr Charles Lemon, Superintendent of

Telegraphs in Wellington ensured government monopoly over electricity service. In June 1883, the Parliament house was lit by a 16-hp gas engine with 300 swan lamps.

In 1882, various electrical companies entered the field. They included Sir Vogel's Australasian Electric Light, Power and Storage Company and the New Zealand Electric Light company. Miles and Company of Christchurch was a successful company at this time lighting Christchurch streets and roadways, the Kaiapoi Woollen Mills and Lyttelton.

The Electric Telegraphic Act consolidated in 1875 and now incorporated in the Electric Lines Act 1884 extended the coverage of legislation to electric lighting of public places and to telephones. The Electric Lines Act ensured proper quality and care of the electric lines.

The first major hydroelectric generation of power in New Zealand was in 1880 and thereafter electricity was used for services other than lighting. Following that, in 1886, Reefton Electrical Transmission of Power and Lighting was formed with 65 shareholders. In August 1888, the first public showing of electrical lighting was held with some incandescent lamps inside the power house. Around the same time, electricity was offered for sale to the public for the first time in New Zealand from sunset to sunrise. Price was on a flat basis of £3 per light and £1 for connection.

In 1892, Reefton Electric Light and Power Company was formed. In 1901, the 30/110V low voltage Crompton dynamo at Reefton was replaced with a new 220V dynamo. Over time more equipment upgrades were made at Reefton with a more powerful turbine installed. The Grey Electric Power Board purchased the company's assets. The quality of electricity supply also became an issue. Thus, the first official inspection of electricity was held in New Zealand by an engineer named H M Miller in 1914.

The first use of AC in New Zealand was at Wellington in 1887 with the introduction of single phase AC at 100 V and 80 cycles/sec. The capacity of the Wellington plant was increased to 1725 W by 1906. In 1903, Christchurch began steam generation from a rubbish incinerator and supplied electricity to the central city area. In 1905, the first steam turbines of New Zealand were built by the Christchurch Tramways Board with two steam generators of 500 kW each.

In the 1890s there were various attempts to use electricity in the mining industry. As a result, electricity was used in coal and gold mining industries as underground power transmission and lighting. The first use of three phase AC was during 1900. By this time, electricity was used in companies other than for mining. Some fifteen factories that produced goods such as aerated water, cordials, furniture and clothing, and painting works were using electricity as a source of motive power. The first municipally owned electricity was in use in 1902 by a plant built in Patea.

5.3 THE INITIAL ROLE PLAYED BY THE GOVERNMENT

During the development stages of electricity, the government did not play a large role besides the regulation of electricity supply. It was only the private companies and local authorities that were much more involved at these initial stages. However, the role the government had played in developing an economic infrastructure and controlling the country's natural resources gave a key reason for involvement in its initiation of electric power generation.

The Public Works Act of 1882 and 1891, controlling the water of rivers and dams, put the control of hydro-electric schemes in the hands of central and local governments. The Electrical-Motive Power Act of 1896 emphasised that any generation or use of electricity for motive power should get permission from the central government. None of the local authorities could grant this permission. This Act also made the government investigate the possibilities of supplying electrical power to the goldfields using waterways. The Water-Power Act 1903 gave the government the sole right to use water for generating electricity. This signalled the government's intention of becoming a producer of electricity.

Peter Seton Hay's report in 1904, with regard to New Zealand's hydro-electric resources, formed the basis for subsequent development of hydro-electric power. The

Water-power Act 1903 and the Electrical Motive-power Act 1896 were incorporated in the Public Works Act 1908. This gave the control of hydro-electric development to both central and local governments. The Public Works Amendment Act of the same year lost some of these controls and allowed private companies to generate and supply electricity, with strict conditions.

Horahora was the first large scale hydro-electric power scheme in the North Island, the largest generating plant in the country at this time, and the first development of the Waikato River that later became very important. The scheme was purchased by the government in 1919 at valuation and extended the plant's capacity to 10,300 kW by 1926. The station was in service until it was submerged in 1947 when the region behind the new Karapiro power station was filled with water.

The demand for electricity increased with an increase of population and the domestic use of electricity. The Dairy Industry Act 1908, establishing a system of herd testing, which needed a lot of clean hot water also increased the demand of electricity. The Aid to Water-power Works Act 1910 authorised the raising of £500,000 by the government for the construction of 'electric power works' and use of water for power generation.

Lake Coleridge, the first major government hydro-electric project, was constructed from 1911-1914 with a head of 490 feet. Initially, four Francis turbines provided enough power to drive 1500 kW generators. The plant proved to be very effective and reliable. As a result, the price of the electricity charges to consumers was reduced to half its original rates. However, the supply on the transmission lines failed several times in the first few years due to unreliability of cheap pin insulators. Several extensions were then made from time to time to the power station. The success of this first government hydro-electric scheme led to several large-scale hydro-electric schemes, which have been in operation thereafter. This gave the concept of an integrated system of stations to provide power across the country.

5.4 TOWARDS A SYSTEM OF ELECTRICITY

Before the government became involved in power generation, it was not feasible to transmit power over long distances. At this time the local authorities built many small power plants which served limited local areas. During the second decade of the twentieth century many more local plants were installed and operated throughout the country.

At the turn of the twentieth century, the Wellington City council decided to install electric trams. Thereafter, many more electric plants were installed and operated in Wellington. During 1925 to 1932, an 80 cycle/sec single phase, 105 V system was successfully changed to a 50 cycle/sec, 230 V system. This was one of the largest system changeovers, which involved around 20,000 customers. The Auckland City Council was also directly involved in power generation at the same time as Wellington, with the commissioning of the Freemans Bay Plant in 1908. However, Auckland was much slower to build a power station. With the formation of the Auckland Electric Power Board in 1921, the demand for electricity usage increased. This forced an increase in the capacity of the plants.

In 1918 Evan Parry proposed the creation of a linked network of electricity with the aim that it would lead to a fully integrated system with standardised voltage supplying a great variety of needs. The report set out planned for a series of large-scale state-provided hydro-electric developments. This proposal was estimated to cost £7.3 million of which £2.1 m would be used to build three new schemes and £4.7 m would be used towards creating a transmission network with substations.

The Electric-Power Boards Act 1918 was passed with the aim of setting a pattern for the reticulation of electricity. It encouraged the dispersion of the existing electricity to cities and towns, with special attention to the extension of power supply to rural districts. However, it was quite clear that for the electricity to get to the country-side, larger, separate district local bodies would be needed.

In 1910 the Water-power Works Account was established. The name was later changed to Electric Supply Account. All loans raised for hydro-electric schemes and income received from the sale of the electricity went to this account. This provided the commercial basis for the government's bulk supply of electricity. The government's financial role was formalised in the State Supply of Electrical Energy Act 1917.

The Municipal Corporations Act 1920 gave the municipalities the right to build power stations, distribute electricity and to transfer funds from their profitable electricity departments to other activities. This was prohibited by the previous Electric-Power Boards Act. The new Act gave a faster track in giving the rural districts early access to electricity. Southland installed the country's first power board and quickly started a major hydro-electric project. Southland Power Board was gazetted in November 1919. This was the first in the country to be gazetted. The whole of Southland was covered except Invercargill. From 1922 to 1925 Monowai Power Station was constructed with two machines, supplying nearly 6,500 consumers. However, the operation of Monowai was never profitable, since both Bluff and Invercargill retained the profits from their sales, taking only bulk supply from the board. The government later purchased Monowai and other Southland Power Board assets.

5.5 ELECTRICITY DEVELOPMENT IN THE NORTH ISLAND

Parry's report played a major role in electricity development in the North Island. The first scheme in Parry's plan was at Mangahao, north of Wellington. Plans for a powerhouse near Shannon were made in April 1917 after the surveys made by G.P. Anderson, Assistant Engineer for hydro-electric schemes in the Public Works Department. However, by that time there was no official commitment to the project. In June 1918, Mangahao Hydro Electric Power League was formed to agitate for an immediate start of the project. There were strong arguments to wait for Parry's reports before starting the project. Parry came to Palmerston North and described his plan for three stations. When he resigned, his work was taken over by Birks.

Testing of the foundations was carried out in 1919 – 1920. By May 1920 most of the access roads to the plant had been completed. Construction of the powerhouse began in April 1922, by which time the surge chamber and pipeline were almost complete. By February 1923, work on the project was carried out 24 hours a day with three shifts. The powerhouse was completed in 1924. The Mangahao station was opened in November 1924, by the Prime Minister William Massey. The total capacity of the plant was 19,200 kW.

Arapuni was the next scheme in Parry's plan after Mangahao. Construction of the powerhouse began in April 1928 and was completed in 1929. The first machine of the Arapuni power station began operating on 4 June 1929. In June 1930 the engineers became aware of a serious problem when a long crack appeared parallel to the river as a huge block of land shifted slightly out and downwards towards the gorge. This led to a considerable controversy. A Swedish consultant, Professor P.G. Hornell, worked on the problem and reported that the site and the engineering work put into Arapuni were excellent. He considered that the location was very suitable for economic power generation, and that the design had made the best possible use of the site's topography. He also concluded that the dam was in the correct position and complied with the main rules that have been used universally.

In January 1931, repair work of Arapuni began as suggested by Hornell. The lake was refilled and the station was started again on 3 April 1932. However, over the years there were a number of problems with the under drainage system. Every failure was followed by further attempts to defeat the water, mainly by extensive grouting through the linings as suggested by Hornell. When a large section of the lining collapsed in 1958, the under drainage system was closed and no further problems were encountered. Arapuni stands as testimony to the ability of early engineers to design and construct a large power scheme on a complex site with little prior experience and much more meagre resources than were available to their successors.

The other location that was attractive from the time of the first surveys was Waikaremoana. This area has a high rainfall and a potential total head close to 1500 feet. However, there was not much participation from the government as it was seen that any development near the Waikaremoana area was a long way into the future. With the formation of the Waikaremoana Hydro Electric League in 1917, there were more attempts to make the proposal a success. Later on, in 1919 the Minister of Public works suggested that the local authorities might start on the project and the government would take over later. In 1926, the Cabinet authorised the Tuai scheme, the first power station on the Waikaremoana.

Overall, Waikaremoana consisted of three power stations, with a total capacity of 124 MW, which were centrally controlled from Tuai. Tuai was constructed from 1926-29 with a head of 676 feet and a total capacity of 52 MW. The second was Piripaua station, which was constructed from 1939-43 with a head of 370 feet and total capacity of 40 MW. The third was Kaitawa station, which was constructed from 1943-48 with a head of 433 feet and total capacity of 32 MW. Each of the plants at Waikaremoana could be run independently from the other two. This marked the completion of Parry's plans for the North Island.

5.6 ELECTRICITY DEVELOPMENT IN THE SOUTH ISLAND

Evan Perry's plans had focused on the North Island. From the mid 1920's the well established South Island stations of Waipori, Coleridge and Monowai were under increasing strain. Investigations in South Island began in 1925, because of the need to supply Canterbury and to take account of the future linkages that would permit supply to Central Otago. These investigations led to the construction of Waitaki power station. Waitaki was constructed from 1928–1934 with a head of 70 feet with an initial capacity of 30 MW. The total capacity was increased to 105 MW by 1954. This helped to satisfy the South Island demand until Roxburgh was finished in 1956. The Other South Island Schemes included Arnold, Tekapo A, Highbank and Cobb River.

Arnold station was build by the Grey Electric Power Board to replace a small coal-fired station near Greymouth. Arnold was constructed from 1929 – 1932 with a head of 42 feet and with a capacity of 3000 kW. The station used the first variable-pitch Kaplan turbines in the Southern Hemisphere. Tekapo A was constructed from 1938 – 1951 with a head of 100 feet and capacity of 25.2 MW.

Highbank was planned by the Ashburton Country Council to provide irrigation between the Rangitata and Rakaia Rivers. Highbank power station was built from 1939 to 1945 with a head of 330 feet. The water drove a single turbine and a generator of 25.2 MW, the largest single unit in operation at that time. Cobb River was constructed from 1937 to 1944 to supply electricity in the northern part of the South Island. The plant was extended from 1949 to 1954 and provided a total capacity of 32 MW.

5.7 PLANNING FOR DEMAND OF ELECTRICITY

During the 1920's electricity was firmly established as a marketable commodity with an increase in generation of electricity, units consumed and growth in the number of consumers. As in other countries, the increase in capacity of generation was aimed to achieve economies of scale by using increasingly large generating units at the centre of the energy source and high-voltage-transmission to load centres. In the case of New Zealand, the energy source was water and high-voltage transmission would allow mass consumption creating demand.

Electricity has been used for all types of needs from manufacturing to domestic life. With the invention of the electric motor, the ways of using electricity increased further. Electricity was used for public lighting and later on for domestic lighting and ironing. More electric appliances were manufactured and began to be used. The first 'All-Electric Exhibition' was held in Wellington in late 1919, with a large number of importers and retailers displaying all the latest household appliances. With the adoption of electric water heating, there was a dramatic increase in the domestic consumption of electricity. With the developments of electricity transmission via power boards, electricity was made available to country districts. A national survey in 1936 indicated that 80 percent of farmhouses had electricity installed.

When the Second World War began, there were a lot of problems faced by the electrical industry. There was no way to install new machines to meet the increase in demand, as no new machines were available at that time. There were even shortages of the spare parts necessary for normal maintenance. Hence, lot of actions were taken by the government to control the use of electricity. The Electricity Control Order of 1942 forbade the use of electric radiators and space heaters during peak hours (Sundays excepted) between May and August at businesses, hotels, theatres and other 'places of amusement' in the North Island.

The wartime regulations were replaced by the Electricity Control Regulations in 1949. The restrictions of the government on power were finally relaxed a little and the public's confidence in the availability of power was restored. There was an explosion in the use of electricity, particularly for domestic purposes. In 1955, the proportion of electricity used in homes reached a peak of over 60 percent, a much higher consumption when compared to Britain and the United States. With technological developments and new technologies of mass production in manufacturing, there was a real decrease in the price of the electrical appliances. This allowed more consumers to use these household appliances and as a result the retail price of the electricity decreased to its lowest level from 1945-50. It then slowly increased in nominal terms, but declined when compared to the cost of living.

From time to time, it had been suggested to plan for the increase in demand. However these suggestions were not taken into account mainly due to the wartime restrictions. The first response to the burgeoning demand was the comprehensive development of the Waikato River. The State Hydro-electric Department was formed in 1946 and took over the Public Works Department responsibility of eliminating electricity shortages and satisfying escalating demand. At this time, it was very difficult to obtain either material resources or workers to construct any new schemes. However, there were a number of projects that were constructed. Maraetai was constructed from 1946-53. Wakamaru was constructed from 1949-56. In the South Island, due to less acute shortages, the massive Roxburgh station on the Clutha River was approved in 1947 and was constructed between 1949 and 1956.

The need for more systematic planning increased as a consequence of severe problems of supply that arose in 1953-54 and due to the increasing demand in the North Island. In 1953 the supply authorities formed a Power and Finance Utilisation Committee to estimate future demand. The committee estimated that there would be an annual increase of 9.8 percent until 1958. It was also estimated that the growth in the North Island would be much faster than in the South Island. In September 1953, Cabinet decided to continue the Atiamuri project but to stop Waipapa, Ohakuri and Braeburn until 1955. Atiamuri was constructed between 1953 and 1958. Ohakuri was approved in 1955 and finished in 1961, and Aratiatia was approved in 1959 and completed in 1964. The Wairakei scheme was approved in 1953 and construction began in 1956.

In 1955 both the government and the supply authorities initiated planning reports. They produced the 'First Report of the combined committee on the North Island Electric Power Supply'. This initiated a system of annual planning reports.

As the demand for electricity continued to increase, a range of thermal projects based on sophisticated new technology and using coal, gas and oil were examined from the early 1960s. As a result, in 1959 Kapuni gas added another dimension to power planning. Thereafter, Otahuhu gas-turbines were approved in 1966 and constructed in the following four years. It was seen that gas turbines were approved as a result of the emergence of steeper peaks in demand. In 1963, when an unexceptionally high increase in consumption of 12.7 percent was reached, the Planning Committee was forced to look beyond hydro-electricity for additional capacity that would be needed by 1968. The Committee proposed a 120 MW gas-turbine plant fuelled by Kapuni natural gas. It was also recommended that all potential hydro-electric sources for the next fifteen to twenty years should be investigated.

Gas reappeared as a source of fuel for the New Plymouth station. Gas disappeared from view in 1967 until the discovery of the Maui field in 1969. The large quantities of gas available led the 1970 Power Committee to re-introduce the possibility of other gas-fired thermal plants. In 1973, due to the dryness of the early months and depleted water storage, some restrictions were again enforced. Electricity allocations had to be reduced by 5 percent, cuts were made in water heating and there were several blackouts in the weekends. Further restrictions were made as a result of the dry summer in 1974.

From 1975, the government became less keen on using gas for electricity and began to explore other possible uses. This led to the so-called 'Think-Big' projects like ammonia-urea, methanol and synthetic petrol plants in Taranaki converting natural gas into a variety of products in the early 1980s. In 1976 the incoming National government changed the parameters of planning with restrictions on government spending. This resulted in a number of projects being deferred. The bulk supply tariff was also substantially increased. More emphasis was also placed on energy conservation. The Electricity Amendment Act No.1 of 1976 made it a goal to reduce the growth of the demand. This was done by promoting measures to achieve greater efficiency in electrical usage. People became more aware of ways to reduce their bills by home insulation and off-peak storage heating.

The demand decreased slowly and it seemed that the days of considerable increase were over. As a result, planners lowered their projections and many planned projects were deferred. In 1978, both Auckland thermal stations were dropped and other than Ohaaki and Clyde, were deferred beyond the horizon fifteen-year planning ahead. Thus the constant search for new stations that had driven planning since the war years was stopped. More emphasis was given on completing the projects that were under construction. The growth in demand fell from 1978 onwards.

In 1980 the Power Planning Committee and the Forecasting Committee combined and produced the first Energy Plan. Their reports suggested considerable additional capacity would be required from 1985. This initiated a number of other projects. The last Energy Plan was published in 1985, and after a less thorough Energy Issues Paper in 1986 the publication of public planning documents of the kind produced since the mid-1950s came to an end. The post-war era of continual construction of new power stations ended after the recent completion of Ohaaki and virtual completion of Clyde.

5.8 THERMAL GENERATION OF ELECTRICITY

Most of the early local power plants generated electricity thermally by means of steam or by the combustion of gas or oil. The main reason behind this was that it was difficult to utilise the hydro-electric resources at that time. There was no means of transmitting electricity over long distances. However, when the transmission problems were solved, from 1950 onwards, the government seriously considered large-scale thermal generation. The main reason behind this consideration was the fact that most of the Waikato River was fully committed to hydro-electricity and future hydro-electric schemes appeared to be too expensive. Natural gas was discovered in the 1960s. The consideration of large-scale thermal generation then changed the shape of the New Zealand electricity generation.

The first major thermal station in New Zealand was Meremere. The station was constructed beside the Waikato River which made it more economical with cooling water instead of using cooling towers. It was constructed from 1956–58 with a total capacity of 210 MW. The plant used up to 80,000 tons of coal a year, and up to 30 million cubic feet of water per day was drawn from the Waikato River for condensing steam and cooling the plant. Meremere used very soft Waikato coal which had a higher proportion of very small particles. It was made worse as the chimneys were only 150 feet high. The emission from this became a major health consideration.

After the Clean Air Act of 1972 the New Zealand Electricity Department had to obtain a special licence from the Minister of Health as Meremere was outside the requirements of the Act. This factor became a strong barrier for approval of more modern thermal power plants, as people did not believe that any others would perform better. With more pressure from the Department of Health to improve its combustion efficiency, the Meremere station was later on operated only part of the year as no improvement could be made without spending several million dollars. In recent years, Meremere was used as a backup station and for voltage support to the Auckland region. In March 1991 it was decided to 'mothball' the power station indefinitely, because it had become increasingly uneconomical to run.

With the growing power needs of Auckland and the predictions of a serious 'dry year' by 1967, the Power Planning Committee in 1963, recommended a new 240 MW oil-fired station at Marsden Point. It was later named Marsden A. It was constructed from 1965-67 with a total capacity of 240 MW, supplied by two 120 MW turbo-alternators. In 1972 the Power Planning Committee recommended another unit at Marsden. This was to cover peak loads and dry year firming of load, because of the lack of progress with the Upper Waitaki development. This became Marsden B, which was constructed from 1976-79 with a 250 MW unit and a boiler that provided 820 tonnes of steam per hour.

With the huge rise in electricity consumption, the Power Planning Committee recommended a second coal fired station near New Plymouth. The site was chosen on the grounds of its harbour. There were no restrictions on chimney height in that area. It was constructed from 1968–74. This was the second largest thermal station in New Zealand at that time. In the early years it was run on oil and later largely using natural gas. The station consisted of five alternators with a total capacity of 600 MW.

Soon after the Second World War, gas turbines were used for electricity generation. The main reason was that they were cheap to build and were ideal for emergency and peak load standby. They can be started and loaded rapidly. Otahuhu gas turbine station was constructed from 1966-70. This was the first large scale gas-turbine in Australasia with a total capacity of 273.5 MW. Stratford gas turbine station was constructed from 1975 – 76 with a total capacity of 220 MW. Whirinaki gas turbine station was constructed from 1975-78 with a total capacity of 220 MW.

In August 1972 the Cabinet Works Committee approved a 1000 MW station at Huntly, subject to an Environmental Impact Statement. By that time the public was more aware of environmental considerations. This was the first major project with such a statement. Huntly station was constructed from 1973 to 1983. This was then the largest power station in New Zealand with a total capacity of 1000 MW. This plant generated more energy than the whole of the Waikato hydro-electric stations. Gas became the main fuel for the station. The shift to a more commercial approach had reinforced its commercial use, by placing greater emphasis on using the cheapest and most readily available source of energy.

5.9 GEOTHERMAL GENERATION OF ELECTRICITY

The idea of geothermal generation also arose soon after the Second World War, when it became apparent that the increase in demand in the North Island could only be satisfied by other sources, in addition to hydro-electricity. New Zealand soon became an international leader in the exploitation of geothermal resources. A Geothermal Advisory Committee was formed in 1949 and proposed a five-year survey of the whole thermal area from National Park to the Bay of Plenty. Later on, in November 1949, investigation of a more promising Wairakei area was recommended.

Wairakei Geothermal Power Station became the second large-scale geothermal generating station in the world and the first to use 'water-dominated' or 'wet' steam. It was constructed from 1956 – 63. The development of Wairakei comprised three stages. Stage 1 consisted of two high-pressure units, two intermediate pressure units and three low-pressure units giving a total capacity of 69 MW. In stage 1A, one further 11.2 MW low pressure unit associated with the pilot hot water plant was added. In stage 2, two more high pressure units were added to station A and three mixed pressure units were added in station B giving a total capacity of 190.6 MW.

The high-pressure units of Wairakei were in operation until they were taken out of commissioning in the early 1980s. In 1988, the addition of 18 MW from Te Mihi development restored the station's output close to its rated capacity. Wairakei proved to be a reliable performer in power generation and has the highest plant factor of any station in the country.

By 1964 it was accepted that Wairakei could not be extended any further, and the increased expenditure was allocated to investigations for a second station. As a result, in 1965, drilling started between Taupo and Rotorua. The name of the station was later changed to Ohaaki. With the small size of the station that could be constructed, there was not much interest for further investigations at that time.

In October 1982, the Cabinet Works Committee approved the construction of the Ohaaki station. The station was completed in 1989. Hot water was produced by 25 wells that were placed on either side of the Waikato River. The station consisted of two high-pressure turbines and two intermediate pressure turbines with a total capacity of 108 MW.

5.10 ECNZ AND ISSUES OF EFFICIENCY

The Electricity Corporation of New Zealand (ECNZ) was formed on 1 April 1987 with the aim to commercialise the government's trading departments. The expectation of the new corporation was that it would perform more efficiently while investing prudently, and that it would lead the way in the reforms under way in the economy.
ECNZ was based around three business units.

1. Electricorp Production – to operate the power stations
2. Electricorp Marketing – to market the energy
3. Trans Power – to operate the national grid.

The fourth unit, PowerDesignBuild, concerned with design and construction, was constituted as a subsidiary company. This was to ensure the transformation of engineering from a decision-making hub to a separate consulting company. The third unit Trans Power was also established later on as a subsidiary company. ECNZ's marketing drive sought to increase the volumes of electricity sold, compete with alternatives such as gas and coal, and achieve a good rate of return for the shareholders.

The low lake inflows of the South Island from November 1991 until June 1992 resulted in a shortage of power. The government cleared ECNZ of the crisis stating that the primary cause of the shortage was the prolonged drought exacerbated by an unexpected increase in demand. However, allegations were made that ECNZ was derelict in its duties for deliberately misusing the system. The Electricity Shortage Review Committee concluded that there was no evidence to support those allegations and gave a strong vote of confidence to ECNZ much to the surprise of all its critics. It was claimed that the occurrence of such a drought was statistically once in 100 years.

The power crisis of 1992 resulted in a loss of public confidence in ECNZ despite the comments made by the government and the Electricity Shortage Review Committee. The media blamed the corporation for the crisis. As a result, the morale inside the organisation declined and staff resigned. Despite the real efficiency gains of the corporation, ECNZ found it difficult to shake off an image of high cost and increasing prices. Thus ECNZ determined to redefine its purpose and accept certain constraints on its commercial objectives. The reshaped strategy that was defined in the Genco report suggested that the company's core business be in the generation and sale of electricity.

The corporation strengthened its emphasis on energy efficiency in its marketing and developed initiatives in association with power companies, to which it had moved closer to after the 1992 power shortage. Thus, it supported the formation of the Energy Efficiency and Conservation Authority in October 1992. The Medallion Award scheme, recognising energy-efficient all-electric homes, had been introduced in the mid-1990. In 1993 the HERO (Home Energy Rating Options) programme provided assessments and advice on improving domestic energy efficiency. By 1995 consultants confirmed that by international standards, ECNZ's stations operated extremely efficiently and at low cost.

ECNZ's determination to establish better public relationships was reflected by its approach to environmental issues. In 1992, as part of this new approach, ECNZ formally committed itself to a set of environmental principals, in which it aimed to be a trusted user of natural resources and resolved to adopt a consultative approach and set high standards of environmental management. It was also among the first group of companies to sign a voluntary agreement with the government in 1995 to reduce CO_2 emissions to within certain targets. Reducing the use of thermal generation and a lower production of CO_2 was consistent with the search for greater efficiency.

Following the 1995 memorandum of understanding leading to the formation of Contact Energy, ECNZ began to sell its smaller regional stations such as Matahina, Mangahao and Lake Coleridge. They also sold both PowerMark and DesignPower. PowerMark had been created from a merger between the electrical contracting arm of Electricorp Marketing and PowerBuild. DesignPower was the engineering consultancy arm of ECNZ.

Between 1987 and 1997, ECNZ was able to improve its overall efficiency by 15 percent, equivalent to 1,000 MW of capacity, by virtue of improved operating and maintenance processes. It was regarded as a highly competitive organisation in New Zealand and overseas. The cost of electricity production also fell when compared to other similar companies overseas. The improved efficiency and excellent commercial performance of ECNZ was reflected by the impact on the wholesale price of electricity. It had fallen in real terms throughout most of the period and in 1998 was 23 percent below the price of 1988.

When the corporation is considered in a wider sense it could be concluded that ECNZ was unable to convince the public or the politicians that the substantial improvement in efficiency presented a case either for leaving the corporation as a single entity or for its privatisation.

5.11 CORPORATISATION AND BREAK-UP OF ECNZ

The formation of ECNZ proved to increase efficiency and was successful as a State Owned Enterprise (SOE). However, its wish for privatisation could not be fulfilled.

The issue of valuation of ECNZ's assets began in late 1986 with the intention of formalising the SOE arrangement prior to corporatisation. ECNZ estimated an initial value of $3.7 billion, based on a private-sector method of assessing value in terms of a ratio between earnings and the price paid for a business in December 1986. Treasury responded in mid-March 1987 with a figure of $8.5 billion, calculated on the basis of the net present value of the discounted cash flow projected over a long time period and with a substantial rise in real prices. After a lot of revaluation, the valuation was finally resolved at the end of March 1988 at a figure of $6 billion plus $300 million for net working capital.

When the matter of asset valuation was resolved, attention was given to the long-term future of ECNZ. The problem in relation to the breaking up of ECNZ was that the different forms of efficiency worked in different directions. It has been argued that a break up would likely diminish both the productive efficiency of the dispatch and the dynamic efficiency of the centralised planning. It would be important to create a combination of conditions that would enhance the overall efficiency. After a lot of arguments between the government and ECNZ, the corporation decided to accept a limited form of break-up as part of a package with privatisation. The corporation wanted to make it clear that an extensive break-up would not only see costs exceeding benefits but also substantially reduce the value of the government's investment.

The issue of electricity pricing came to command public attention in 1991. New Zealander's were concerned about pricing with the long-standing expectation that electricity was a cheap service provided by the state. It was decided in July 1988 that the price increases must be below the inflation rate so that the price gradually declined in real terms. When the price was reduced by 20 percent by 1991, ECNZ was forced to revise its thinking as it became a risky political issue. Thus the customers were notified that the price would increase by 3 percent that year. However this rate was reduced to a 1.5 percent increase after various disagreements regarding the price increase.

At this time, ECNZ felt that the forces supporting privatisation had actually strengthened. However, the National government elected from mid-1991 effectively set itself against privatisation. In October Jim Bolger, the Prime Minister, indicated that privatisation was off the agenda, at least until after the next election. The work of ECNZ was redirected to developing the wholesale electricity market, the pricing strategy, and retail reforms.

Following the final deregulation of the retail sector with the removal of franchises in April 1994, Trans Power became a separate SOE on 1 July. Trans Power was valued at

$3 billion with $1.8 billion of debt, which needed to be repaid by December 1996. With the reorganisation of Trans Power, the debt was successfully repaid within that period.

The Wholesale Electricity Market Study (WEMS) was formed in 1992 as a result of a new spirit of co-operation in the industry. The WEMS group attempted to find a middle ground that would provide signals for both building new capacity and adopting energy efficient technologies, while protecting consumers, through a combination of contracts and spot-market pricing. The Wholesale Electricity Market Development Group (WEMDG) was formed in mid-1993. Its study concluded that a competitive market would be the best means of achieving new generating capacity. The Electricity Market Company (EMCO) was formed in August 1993 from power companies and ECNZ, together with independent directors. EMCO had the task of first developing and then operating the wholesale pool and spot market from 1 October 1996. The market began to operate in October 1996 as planned.

The issue of the break-up of ECNZ was raised again when the government announced a review of break-up options in the June 1997 Budget. Thus it was almost certain that the corporation was to be split again. However, ECNZ opposed the idea saying that it was too early for a review. When Jenny Shipley replaced Bolger as the Prime Minister in November 1997, asset sales and increased competition became more important to the government. On 7 April 1998 the government announced that it had decided to break up ECNZ into three parts and to separate the line and energy businesses of power companies. There would be a North Island hydro group comprising eight Waikato stations, with 13 percent of total national capacity; another North Island group consisting of Huntly and the Te Awamutu stations of Tokaanu and Rangipo, with 17 percent of capacity; and a South Island group of eight Waitaki hydro stations and Manapouri, with 30 percent of capacity. The remainder was 27 percent with Contact Energy and 13 percent with other generators.

To plan the implementation of the break up, an Electricity Reform Transition Unit (ERTU) was formed. With the collapse of the coalition government in August 1998 the issues of asset sales and privatisation came into the political agenda. The government soon announced the investigation of Contact Energy for sale. With the separation of the retail line and energy businesses, the restriction on retail involvement by ECNZ and Contact Energy was lifted. Thus to reduce risk, many power companies decided to divest themselves of the energy component of the businesses.

Contact Energy moved quickly and announced that it would start retailing in Auckland, Wellington and Christchurch. The newly formed First Electric (a subsidiary of ECNZ) announced that it too would compete for retail customers by offering cheaper rates. ECNZ was split into three State-Owned Enterprises (SOE's), Genesis Power, Meridian Energy and Mighty River Power, on 1 April 1999 [MED_EMPG, 2002] [MED_EMPG, 2001].

5.12 RECENT CHANGES OF THE ELECTRICITY INDUSTRY

On September 1998, the government announced its decision to sell Contact Energy. In March 1999, 40% of the shares of Contact Energy was bought by Edison Mission Energy based in the United States for $NZ 1.208 billion and the remaining 60% was sold to the public [MED_EMPG, 2002] [MED_EMPG, 2001]. The three state-owned electricity generators Meridian Energy, Genesis Power and Mighty River Power decided to expand their business into the retail market. The two former integrated distribution and retail companies, TrustPower and TransAlta, also started retailing.

The Electricity Industry Reforms Act 1998 required electricity companies to separate line and supply business by 31 December 2003 [MED_EMPG, 2002] [MED_EMPG, 2001]. Most electricity companies decided to retain their line business and sell their retail business. TransPower, a state-owned enterprise, is responsible for operating the national grid and to contract with users for new investment opportunities [MED_EMPG, 2001].

Under the Commerce Act 1986, the electricity sector, like any other business, has to comply with New Zealand's general competition law. This Act applies to all individuals and commercial organisations including the state-owned enterprises. In addition, industry-specific regulations like Electricity (Information Disclosure) Regulations which was substantially strengthened in April 1999, discouraged anti-competitive and rent-seeking behaviour by line businesses (TransPower and local distributors) [MED_EMPG, 2002] [MED_EMPG, 2001]. This was done by making such behaviour transparent and facilitating further regulatory action or recourse to the Commerce Act.

The Electricity Industry Bill was passed in August 2001. The Bill amended the Ministry of Energy Abolition Act 1989, the Commerce Act 1986, the Electricity Act 1992 and the Electricity Industry Reforms Act 1998. The Commerce Amendment Act 2001 allowed the Commerce Commission to control the price revenue of electricity line businesses and to take over the administration of the electricity information disclosure regime. The Electricity Amendment Act 2001 allowed the government to establish by Order as a Crown entity, an Electricity Governance Board and provided the government with the power to make regulations on a number of matters like the requirement to provide domestic consumers with a low fixed charge tariff option [MED_EMPG, 2002]. The Electricity Industry Reform Amendment Act 2001 relaxed the rules on the ownership of the electricity generation by line companies and enabled unlimited ownership of renewable generation.

The sale and purchase of wholesale electricity in New Zealand is organised by the participants in a private sector wholesale market [MED_EMPG, 2002]. Spot prices are set half hourly, 2 hours in advance, to match supply and demand. Generators and buyers also hedge against spot prices for most of their supply and demand [MED_EMPG, 2002].

5.13 SUMMARY

This chapter has described the developmental changes in the New Zealand electricity industry. The thesis focuses on proposing a number of forecasting models for electricity consumption in New Zealand, the United States, the United Kingdom, the Maldives and various regions of the world. Although the pattern of actual electricity consumption is not greatly affected by the various regulations and the changes that occur in the electricity industry as shown previously in Chapter 2, an understanding of New

Zealand's electricity industry could help to explain the behaviour of the models when applied to the electricity consumption data of New Zealand. This may also help to explain the situations in other countries to some extent. In addition, this serves as an indicator of the various phases an electricity industry has undergone during its development.

Chapter 6

APPLICATION OF THE MODELS TO NEW ZEALAND

6.1 INTRODUCTION

New Zealand has a unique electricity industry with few legislative and Government restrictions on constructing power stations, power lines or supply to customers. Although the industry is unique, and there are minor differences in the developmental changes, it does not exclude the fact that it is representative of the overall changes in the development of industries in other countries. The chapter begins by describing the pattern of electricity consumption in New Zealand. The proposed forecasting models are then applied to electricity consumption in New Zealand. Firstly, the Logistic model is applied to New Zealand. The Logistic model is further studied by varying the saturation levels. The electricity consumption in New Zealand is then modelled using economic and demographic variables in the regression models. Thereafter, the traditional autoregressive integrated moving average (ARIMA) technique is applied to electricity consumption. Thereafter, the Harvey Logistic and Harvey models are then applied to the electricity consumption data. Finally, the Variable Asymptote Logistic (VAL) model is applied to the electricity consumption. The chapter describes in detail the steps involved in applying the models to electricity consumption and the results of the statistical tests used in validating the models. The models are then compared for their goodness of fit and forecasting accuracy. The chapter concludes by presenting and discussing a set of forecasts by the six models for a period of 15 years ahead and comparing them with the available national forecasts for New Zealand.

6.2 ELECTRICITY CONSUMPTION IN NEW ZEALAND

The data used in this research consists of the annual electricity consumption data for New Zealand, expressed in Gigawatt-hours (GWh). The historical period involved from 1943 to 1999, amounted to all the reliable data available as at July 2002. The nomenclature used is such that a year, say 1975, referred to the financial year from 31 March 1975 to 31 March 1976. The consumption data was obtained from the Energy Planning Report [Ministry of Energy, 1982-84] published by the Ministry of Energy and the Energy Data File [MED, 2002] published by the Ministry of Economic Development. Since the Ministry of Economic Development is not satisfied with the integrity of the data available for the year ended 2001 at the time of publication, that data has not been used in this research.

The electricity consumption data obtained has been categorised into three sets for the purpose of this research. They are:

1. Domestic sector consumption,
2. Non-Domestic sector consumption, and
3. Total consumption.

Domestic and Non-Domestic sectors are often studied separately because of their perceived difference in contribution to society. The Domestic sector of residential customers is primarily a goods and services consumption sector of society while the Non-Domestic sector is goods and services and hence that which gives rise to the generation of economic wealth of a country. It nevertheless consumes electricity (and other resources) in generating that wealth. The Total consumption is simply the total electricity consumed and is the aggregate of Domestic and Non-Domestic sector consumptions. The electricity consumption for New Zealand from 1943 to 1999 is shown in Figure 6.1. The exact values of electricity consumption for the various sectors are given in Appendix A. As seen from Figure 6.1, there is an increase in trend in the consumption data for all the sectors. However, the rate of consumption growth is generally very slow in the Domestic sector especially from 1975 onwards.

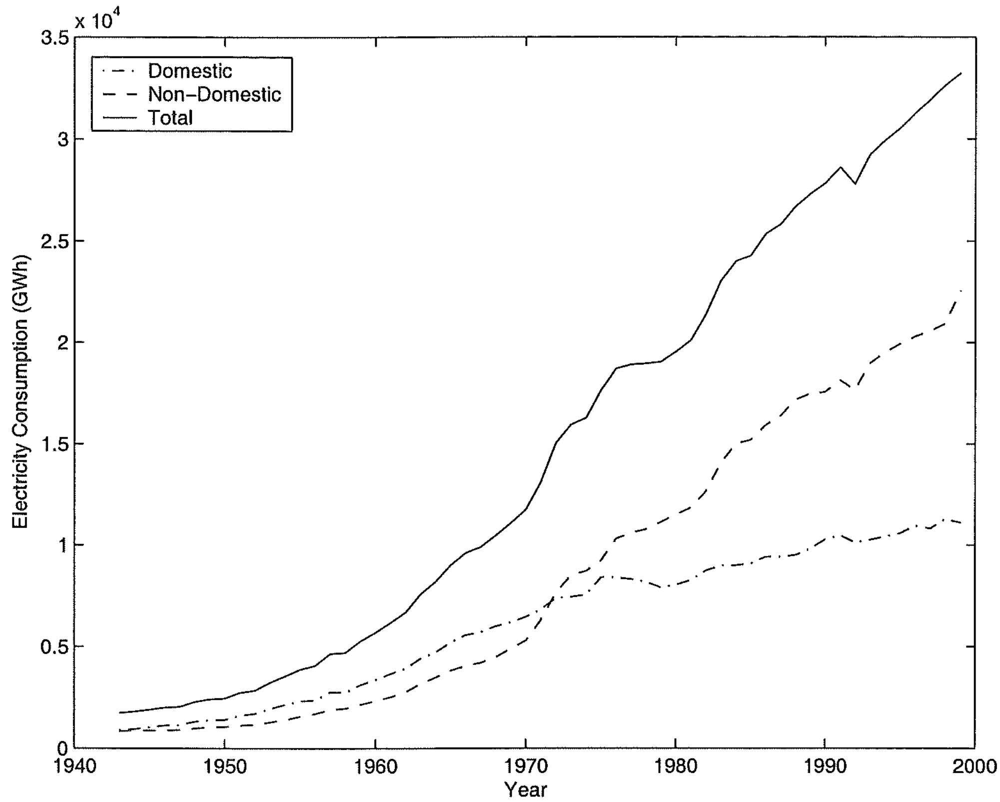

Figure 6.1 Electricity consumption in New Zealand

The restrictions on electricity brought by the prolonged drought sequence from November 1991 to June 1992 [ESRC, 1992] can be clearly seen on all sectors with a sudden decrease in electricity consumption for 1992.

6.3 APPLICATION OF THE LOGISTIC MODEL

6.3.1 Autocorrelation Analysis

Autocorrelation analysis was performed for New Zealand electricity consumption data, before applying the Logistic model. A summary of the r_k values for time lags k =1, 5, 10 and 15 for New Zealand is given in Table 6.1. While there is a decrease in the value of autocorrelation coefficients for an increase in time lag, the coefficients for all the data sets indicates that they are high even at the 15 year lag. Thus, forecasting using time trend extrapolation of the present data can be applied as there is significant autocorrelation in the consumption data.

Table 6.1 Autocorrelation coefficients for New Zealand

Sector	Autocorrelation Coefficient, r_k			
	k =1	k =5	k=10	k=15
Domestic	0.977	0.883	0.761	0.639
Non-Domestic	0.963	0.826	0.659	0.491
Total	0.970	0.848	0.701	0.553

6.3.2 Application to Electricity Consumption

The Fibonacci search technique is applied to all the three sets of electricity consumption data in New Zealand. A MATLAB program has been developed that performs the Fibonacci search technique and produces the required results. The accuracy of the developed program was verified by comparing it to results previously obtained using the same data [Tay, 1985]. Asymptotic values are calculated using the entire sets of historical data available from 1943 to 1999. Table 6.2 shows the values of the asymptotes and the corresponding SSR values.

Table 6.2 Logistic model asymptotes and the corresponding SSR values for New Zealand

Sector	Data Year	F (GWh)	SSR
Domestic	1943 - 1999	11420	6.47×10^6
Non-Domestic	1943 - 1999	24573	1.19×10^7
Total	1943 - 1999	36563	1.87×10^7

When the Fibonacci search technique was applied to the New Zealand data from 1943 - 1981 [Tay, 1985], the asymptote for the Non-Domestic sector (F = 41621 GWh) was greater than that for the Total Consumption (F = 32452 GWh). There are two possible explanations for this result that has been suggested [Tay, 1985]. The first was that it might have been the effect of the inclusion of the electricity-intensive industries in the

Non-Domestic consumption data, the second being that the consumption has not gone beyond the early stage far enough for a reliable Fibonacci optimal search to be applied.

The calculated asymptotes in Table 6.2 show that the asymptote for the Non-Domestic sector is below that for the Total consumption. This is a clear indication that the Non-Domestic sector has gone beyond the early stage of development, and thus the second explanation seems to be very appropriate. Moreover the aggregated sum of the Domestic and the Non-Domestic sector's asymptotes is 35993. This is within 2% of the asymptote calculated for the Total consumption and indicates that both sectors and the total are well beyond the early stages of development and are reaching maturity.

By using the calculated asymptotes, the Logistic model is fitted to each of the historical data sets. The fitted Logistic curves for the Domestic and the Non-Domestic sectors and the Total consumption are shown in Figure 6.2, Figure 6.3 and Figure 6.4 respectively.

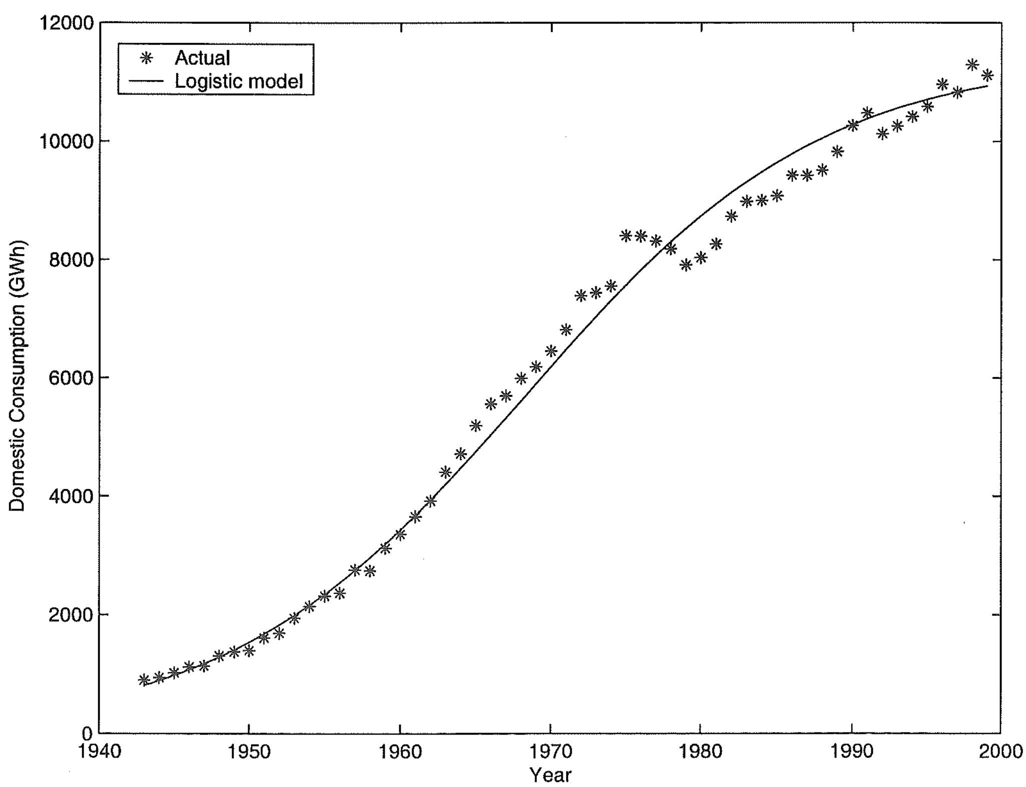

Figure 6.2 Fitted Logistic model for the Domestic sector of New Zealand

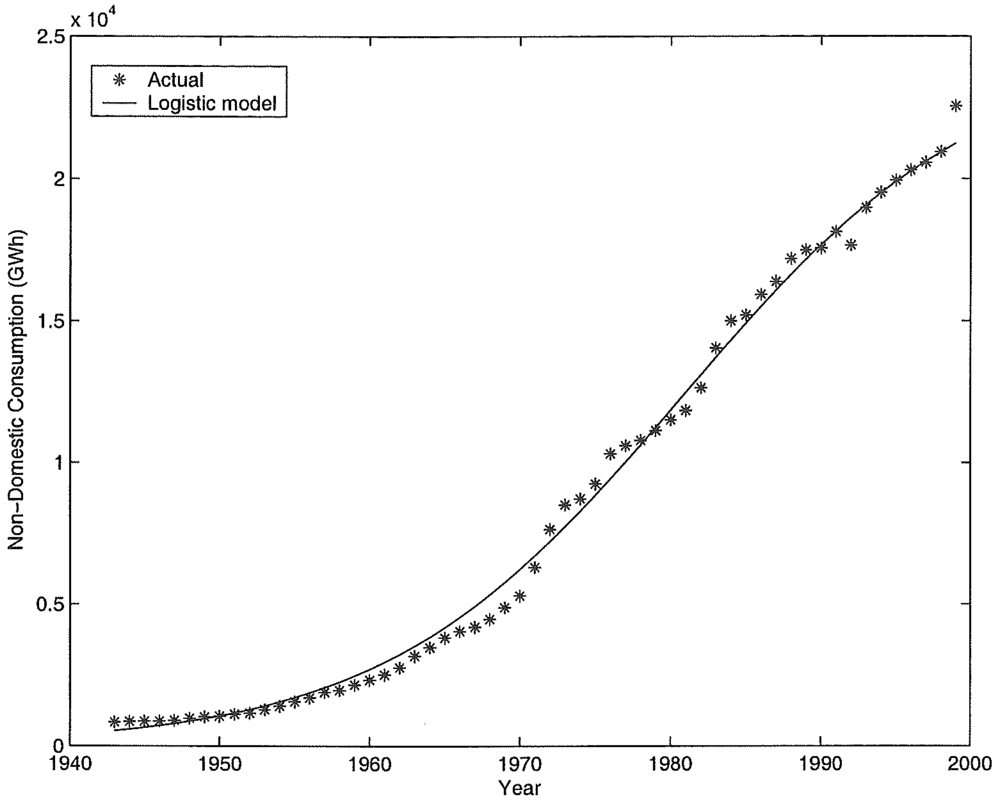

Figure 6.3 Fitted Logistic model for the Non-Domestic sector of New Zealand

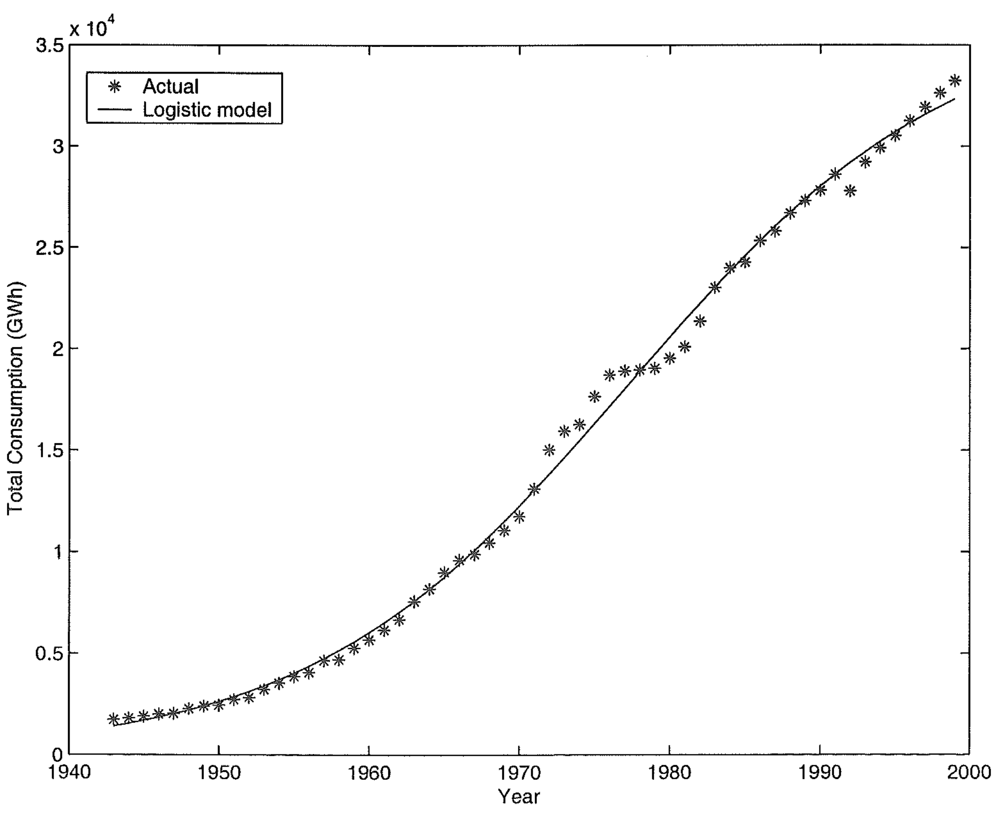

Figure 6.4 Fitted Logistic model for the Total electricity consumption of New Zealand

The developed Logistic models have given very good fits of the historical electricity consumption in New Zealand for both the sectors and Total electricity consumption.

6.3.3 Comparison with Historical Forecasts

The forecasts made by the Electricity Sector Forecasting Committee (ESFC) [Ministry of Energy, 1982-84] for New Zealand with the corresponding forecasts of the Logistic model [Tay, 1985] using electricity consumption data up to 1981 are compared. Since the actual consumption data from 1982 are now available, these forecasts are compared with the actual data that has subsequently been accrued. All the forecasts are obtained for 15 years ahead assuming that the last known set of data available was for 1981. Figures 6.5 to 6.7 show the actual consumption data along with the ESFC forecasts and the Logistic model forecasts for the Domestic and the Non-Domestic sectors and the Total consumption respectively. Figure 6.8 shows the percentage variation of the two forecasting methods compared with the actual data for the Domestic and the Non-Domestic sectors and the Total consumption. The percentage variation is calculated using

$$Variation(\%) = \frac{Actual - Forecast}{Actual} \times 100 \tag{6.1}$$

For the Domestic sector, the two sets of forecasts have underestimated the actual consumption over the entire forecast period. The Logistic model has given better forecasts for the initial 6 years, but the variation in error has increased more than that for the ESFC forecasts for the longer term forecasts.

For the Non-Domestic sector, both the sets of forecasts have overestimated the actual consumption. The Logistic model has generally given closer estimates than the ESFC forecasts, but both show significant departures from what has occurred. The electrification of commerce and industry has not proceeded at the rates predicted at that time.

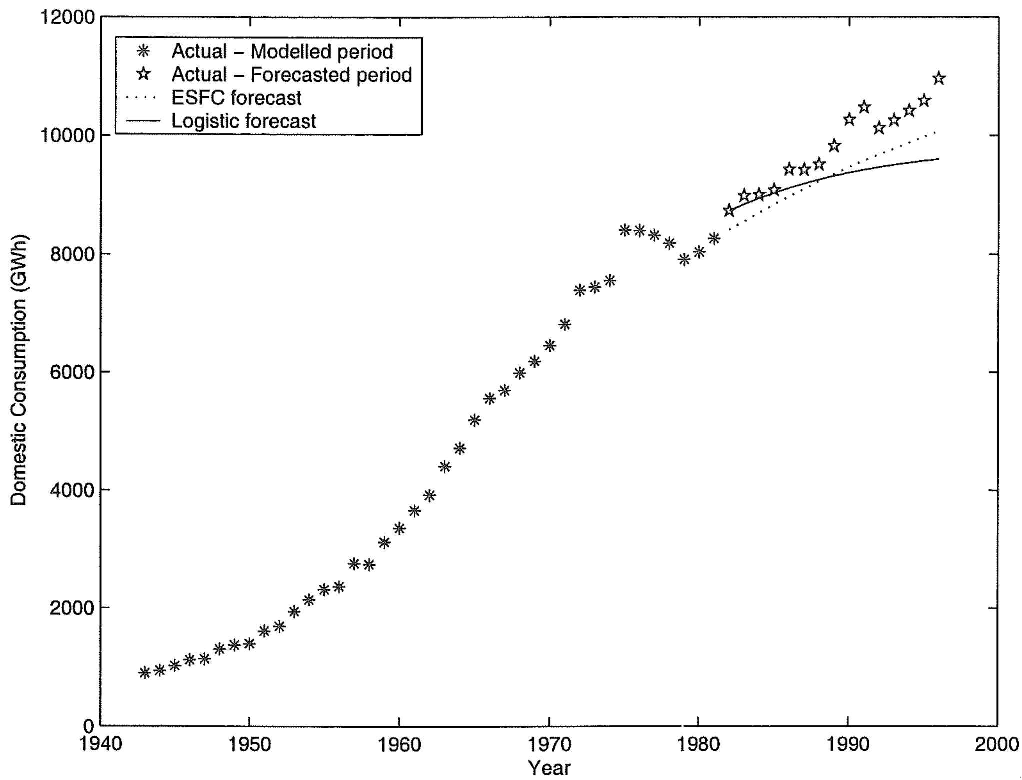

Figure 6.5 Comparison of Logistic model with ESFC forecasts for Domestic sector

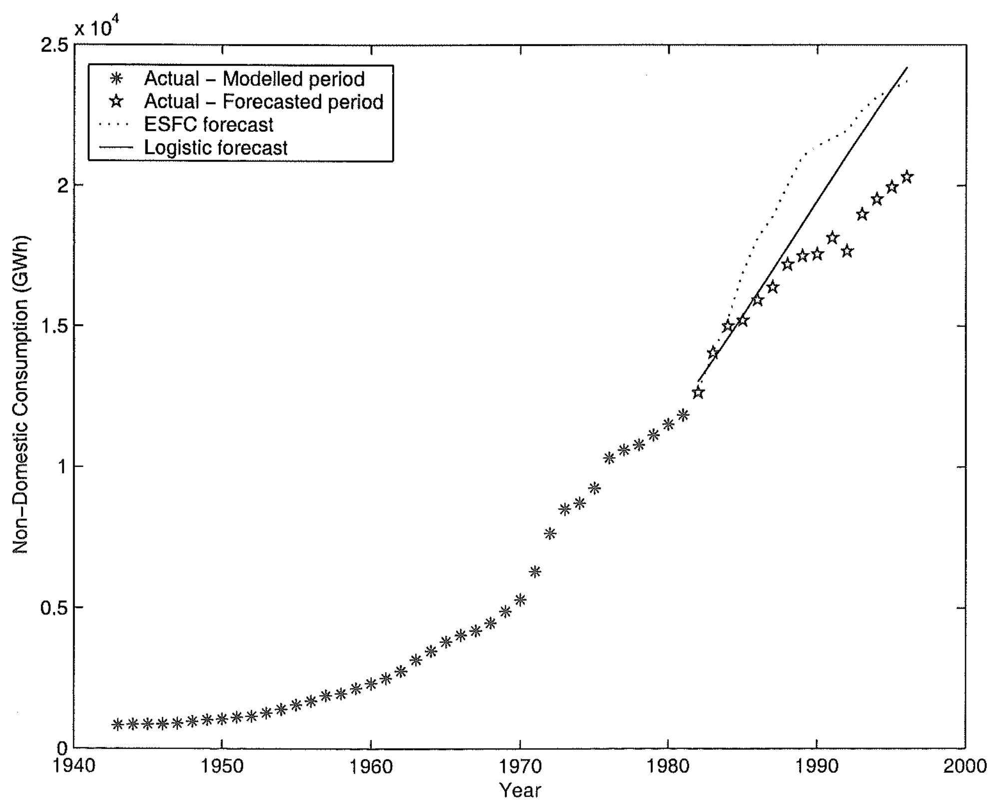

Figure 6.6 Comparison of Logistic model with ESFC forecasts for Non-Domestic sector

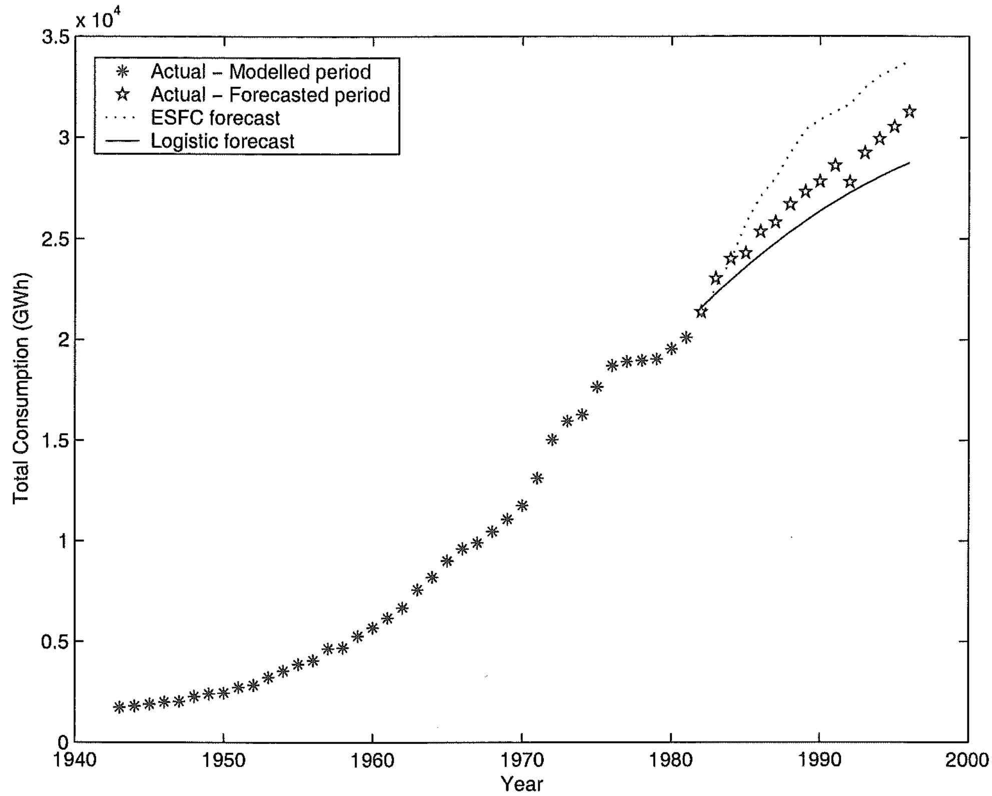

Figure 6.7 Comparison of the Logistic model with ESFC forecasts for the Total consumption

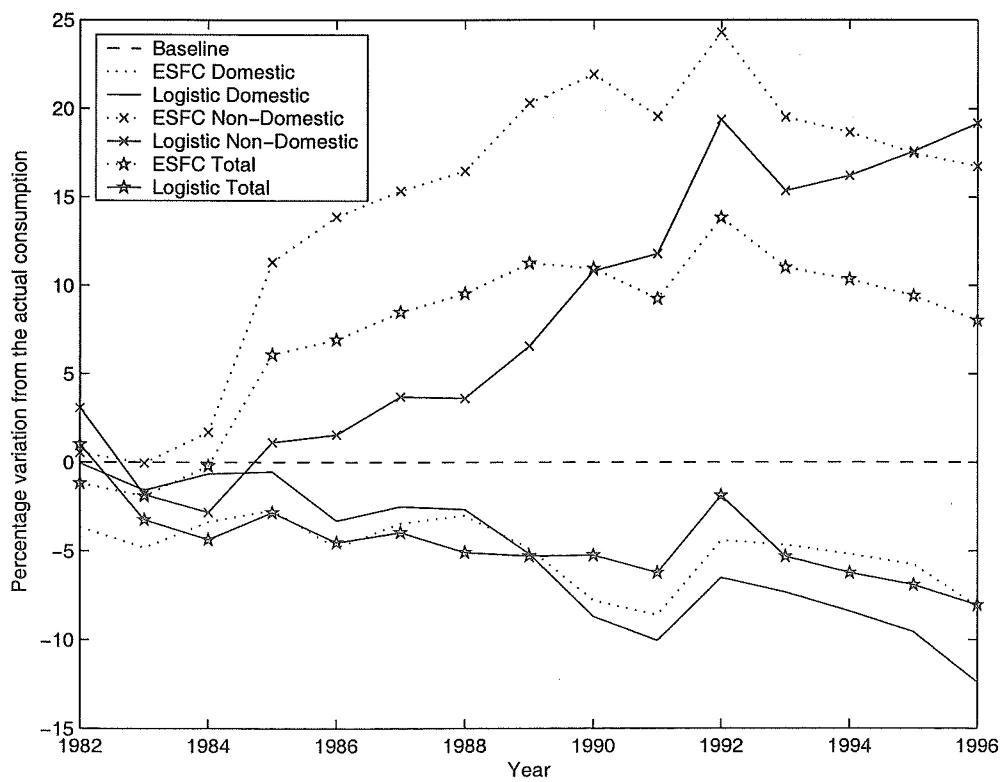

Figure 6.8 Percentage variation of the electricity consumption compared with ESFC and Logistic models

The forecasts for the Total consumption are more diverse. The ESFC forecast has overestimated, while the Logistic model has underestimated the actual total electricity consumption. As for both the Domestic and the Non-Domestic sectors, the Total consumption forecasts are better by the Logistic model. The error variances for the Logistic forecast lie within 7.5%, while those for the ESFC forecasts lie within 13% over the whole range of data. The ESFC model adopts the aggregate of the Domestic and Non-Domestic forecasts to get the Total consumption forecasts, while the Logistic model is fitted directly to the historical Total consumption data.

6.3.4 Effect of Historical Data on the Asymptotic Value

The forecasts made by the Logistic model are significantly affected by the asymptotes that are obtained by the Fibonacci search technique. Once the historical data is used to get the best fit, i.e., to get the constants of the regression equation, it is the upper limit, F, which determines the upper limit of the forecasts in the long term. While, the Fibonacci search technique used to get the asymptote has been proven to be an effective method [Tay, 1985] the value of F will depend on the extent of the data used in determining it. This section analyses how the historical data used for the three data sets effects the asymptotic value and consequently is reflected on the predicted consumption values.

Asymptotic values are generated for the Domestic and the Non-Domestic sectors and the Total consumption by using data values up to a particular year. For each of the asymptotic values obtained, the base year is 1943. Thus, the asymptotic value for year 1987 is the asymptotic value obtained by the Fibonacci search technique for the years 1943 – 1987. Table 6.3 shows the asymptotic values obtained for a number of selected years.

The year 1981 was chosen as this represents the extent of data available in previous studies [Tay, 1985] [Bodger and Tay, 1987]. The year 1987 was chosen as this was the year that marked the introduction of deregulation of the electricity industry in New Zealand. The subsequent years of 1992, 1997 are at 5 year intervals and 1999 is the extent of reliable historical data available. By using these asymptote values forecasts can be made for the future years. Figure 6.9, 6.10 and 6.11 show the forecasting lines for each of the Domestic, the Non-Domestic and the Total consumption data respectively for each of the selected years.

Table 6.3 Sets of asymptotic levels for Domestic, Non-Domestic and Total consumption

Year	Asymptotic Value (GWh)		
	Domestic	Non-Domestic	Total
1981	9836	36775	32448
1987	9846	29568	33739
1992	10578	23092	34312
1997	11124	24473	35681
1999	11420	24573	36563

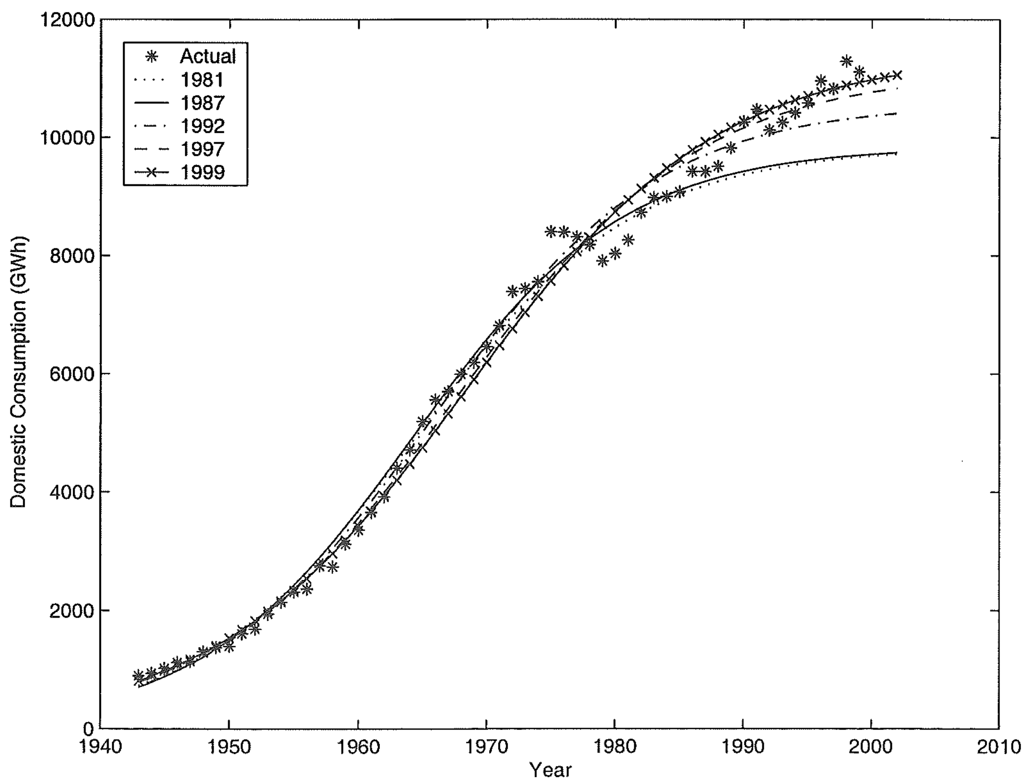

Figure 6.9 Effect of historical data on the asymptotes for the Domestic sector

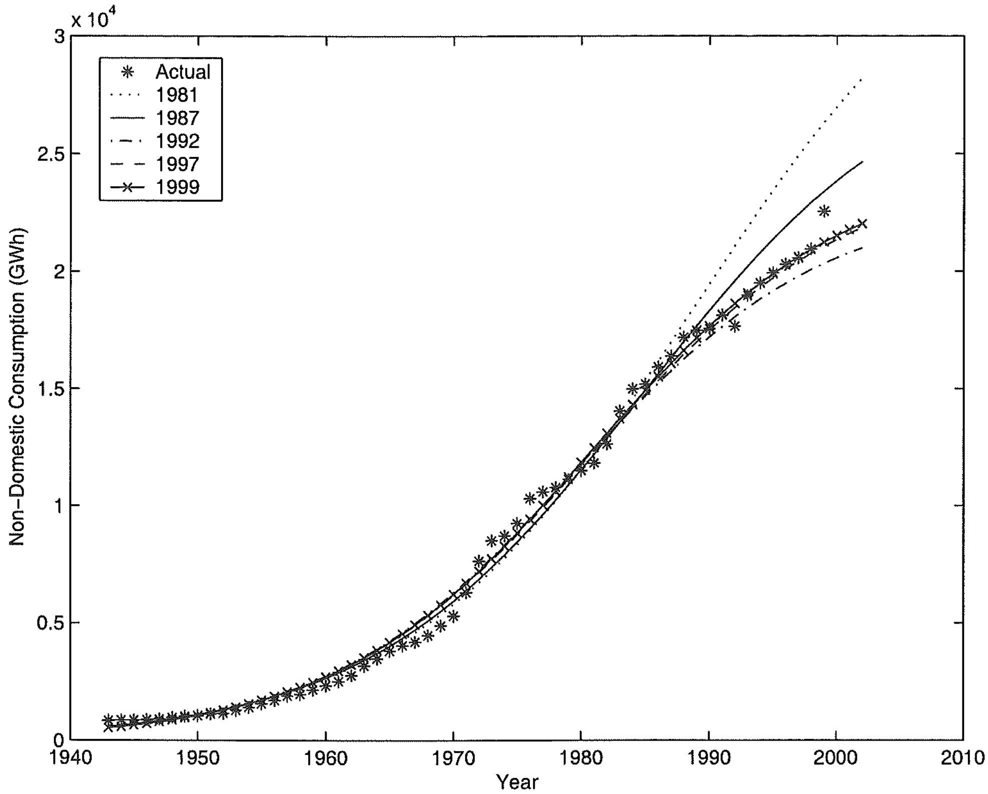

Figure 6.10 Effect of historical data on the asymptotes for the Non-Domestic sector

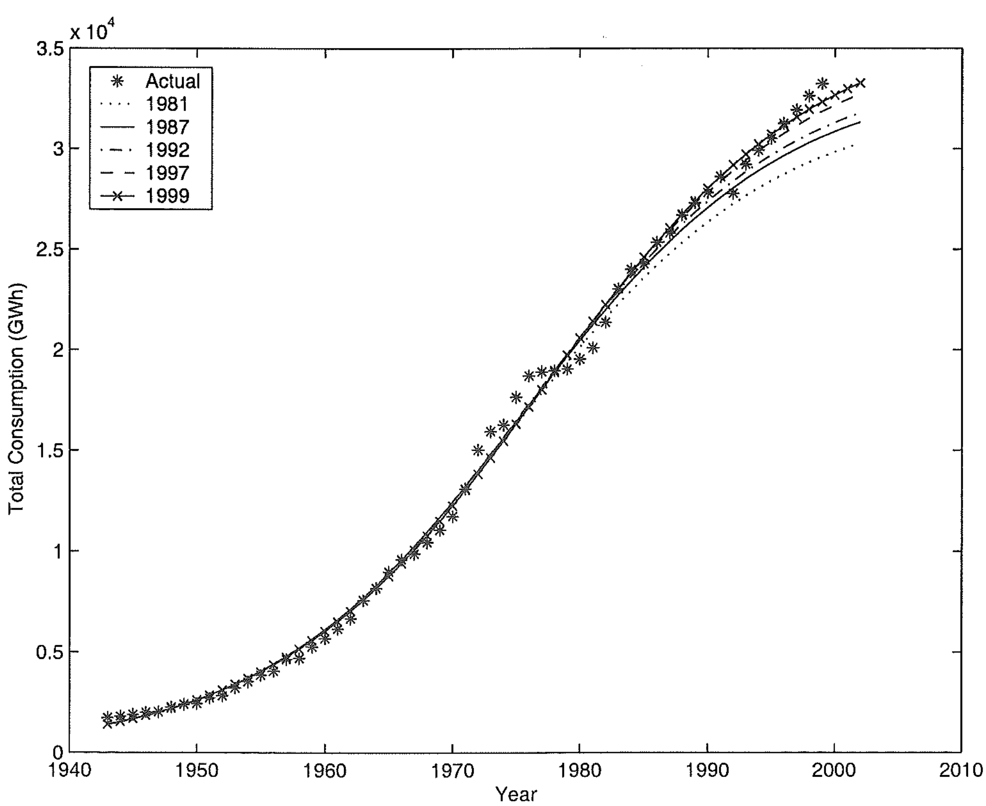

Figure 6.11 Effect of historical data on the asymptotes for the Total electricity consumption

For the Domestic sector, the forecasts for 1981 and 1987 are very similar. Increasing the historical data used has given very comparable forecasts for subsequent years. As the extent of the historical data used increases beyond 1987, the forecasting lines increase in value. This is a direct result of the actual increase in Domestic consumption in the more recent years. Although the aggregate electricity consumption pattern was not significantly affected by the introduction of deregulation in the electrical industry of New Zealand in 1987 (Chapter 2), this indicates that the Domestic electricity consumption might have been affected to some extent.

The Non-Domestic sector shows that it has yet not reached maturity in the initial forecasts. The high asymptotic value for 1981, which is even higher than that for the Total consumption, shows that Non-Domestic sector is in its early years of growth. As the amount of historical data used increases there is a consistent decrease in asymptote values. This is mirrored in the forecasting lines resulting in lower consumption values. It is worthwhile noting that the asymptote value for 1999 is higher than that for 1997. This indicates that the Non-Domestic sector is possibly reaching maturity as in the Domestic sector. However, there is not enough data for this speculation to be conclusive.

The forecasts for the Total consumption appear to be more stable in general than the two sectors. Although there has been consistent increase in the asymptotic levels for each of the consecutive 5 years, the resulting increase in the asymptote value is very small. This is reinforced from Figure 6.11, as very similar gap lengths separate the forecasting lines. As for the Domestic sector, the Total electricity consumption might be reaching maturity.

The asymptotic levels have steadily risen over the years as more and more data is used in the calculation. This implies that the residential customers have increased the electrification of their homes. By contrast, the asymptotic value for business and industry has generally decreased indicating a decrease in electrification although this pattern is significantly affected by the data moving away from the earlier growth years. The asymptotes for the Total consumption has increased with increasing data reflective of society as a whole increasing electricity consumption beyond what was predicted in 1981.

As can be seen from each of the data sets, there has been a significant effect on the asymptotes when the amount of historical data used is increased. For the Domestic sector and Total consumption, there has been a generally consistent increase in F every year. This implies that original predictions underestimated the continued growth of what could have been considered as sectors approaching maturity. For the Non-Domestic sector, the asymptotes have decreased as the amount of data used increase. This implies that this sector was initially immature but may now be approaching maturity.

6.4 ECONOMETRIC MODELS FOR NEW ZEALAND

The proposed econometric models are applied to the electricity consumption data in New Zealand. First simple linear regression models are proposed using GDP and the price of electricity. The Combined model, involving the multiple liner regression analysis, is then proposed using population, price of electricity and GDP. In the case of New Zealand, very detailed analysis of the modelling involved is described. In addition, the simple linear models will only be proposed for New Zealand. This is to serve as a guide on how simple regression analysis may be used to forecast electricity consumption. Therefore, the results of the simple regression models will not be extended beyond this section. The Combined model will be used in comparison with the other models and applied to the other countries as this is a more frequently applied technique and allows the effects of more than one variable on electricity consumption.

6.4.1 Linear Models Based on Gross Domestic Product

Gross domestic product (GDP) is a measure of the value added from all economic activity in a country and can thus be regarded as a variable that represents the national wealth of a country. Economic growth, expressed in terms of GDP, has a considerable influence on the forecasts of all energy forms [Ministry of Energy, 1982-84]. GDP has also been used as an appropriate indicator of the investment consumers make in electric apparatus [Skiadas *et al.*, 1993]. Correlation of GDP and some other socio-economic factors led to the conclusion that these factors could be used in predicting electricity consumption [Skiadas *et al.*, 1993]. Therefore, GDP is used as a measure of the general wealth of New Zealanders and thus represents their investments in the electricity industry as residential or commercial consumers.

GDP data for New Zealand was obtained from Statistics New Zealand [Department of Statistics, 2000 & 2002] [Statistics New Zealand, 2002]. The actual GDP data in real terms is included in Appendix A. Two different models based on GDP are developed as GDP values are available in both current and real values. The earlier model is referred to as the *Current GDP* model while the latter is referred to as the *Real GDP* model. The real values are those adjusted for inflation.

6.4.1.1 Current GDP Model

Figure 6.12 shows New Zealand GDP at current values from 1963 to 1999. The GDP values are in millions of New Zealand dollars. The GDP value for say year 1999 refers to the data for the year ended March 2000. This is consistent with the way the electricity consumption data for New Zealand has been collated. The GDP values initially increased slowly in an exponential growth fashion, but then the pattern of growth changed from about 1980 onwards.

The question arises as to whether all the relevant data or part of the data should be used in developing the simple linear models. There is little evidence to support the principle of using all relevant data [Armstrong, 2001]. However, there is some evidence to suggest that having too few data points is detrimental [Dorn, 1950] [Smith, 1990]. While extrapolating annual consumer product sales it has been concluded that using more data did not significantly improve accuracy [Schnaars, 1984]. Since the data does not follow a linear trend if the whole data set is chosen and assuming that the later years are more significant in representing the future, GDP values from 1980 to 1999 are used in this section to propose the Current GDP model as using all the historical data cannot provide a statistically acceptable model. Figure 6.13 shows the GDP values from 1980 to 1999 along with the fitted straight line. Simple regression analysis is used to obtain the best fit line. The equation of the fitted line is

$$G = -8.82\times10^{6} + 4.47\times10^{3}t \tag{6.2}$$

where,

G = Gross domestic product (NZ$ millions), and

t = time in years from 1980

Electricity Consumption versus GDP

Figure 6.14 show the plots of the GDP and electricity consumption for the Domestic and Non-Domestic sectors, and the Total consumption respectively along with their fitted lines. For each of the sectors, the fitted line is of the form:

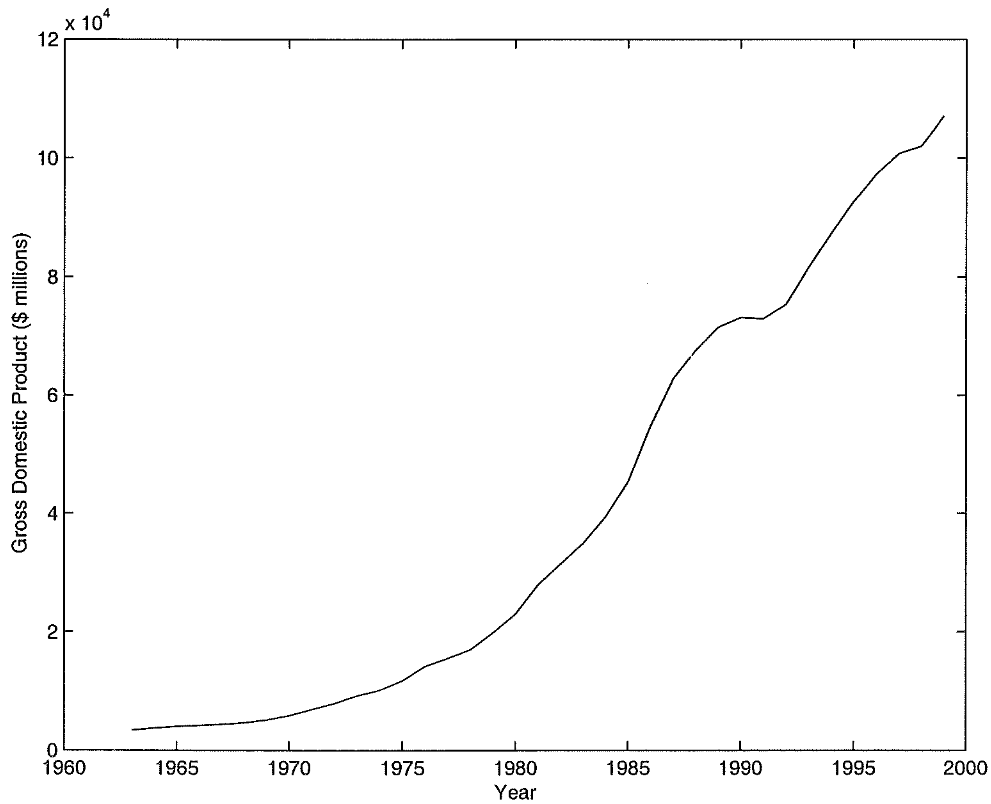

Figure 6.12 GDP for New Zealand in current values from 1963-1999

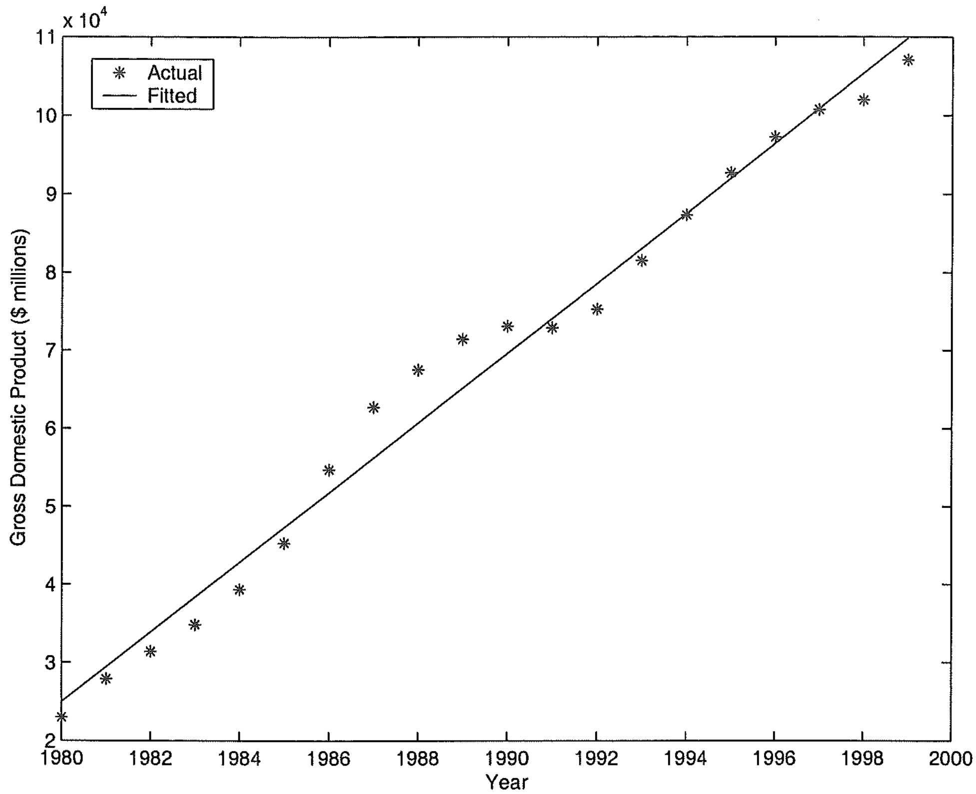

Figure 6.13 Current GDP for New Zealand (1980-1999) with the best fitted straight line

$$Y = a + bG \tag{6.3}$$

where,

Y is the electricity consumption in GWh

a and b are coefficients as shown in Table 6.4 and

G is the GDP expressed in millions of dollars.

Table 6.4 Coefficients of the electricity consumption versus current GDP

Sector	a	b
Domestic	7.49×10^3	0.035
Non-Domestic	9.39×10^3	0.115
Total	1.68×10^4	0.151

Figures 6.14 shows good straight line fits for electricity consumption versus GDP over all sectors. Table 6.5 summarises the correlation coefficient, coefficient of determination and results for *F*-test and *t*-test along with the corresponding critical values.

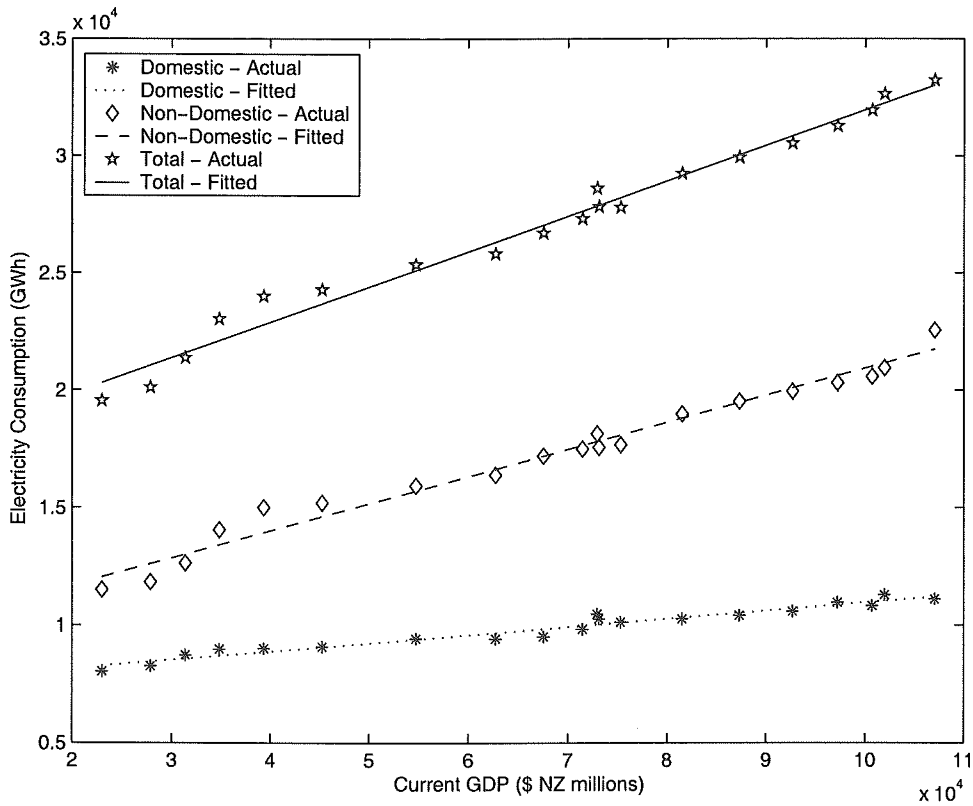

Figure 6.14 Electricity consumption against current GDP (1980-1999)

Table 6.5 Statistical results of electricity consumption versus current GDP (1980-1999)

	Correlation coefficient	r^2	*F*-test 99% value	*F*-test *F*	*t*-test 99% value	*t*-test *t*
Domestic - GDP	0.976	0.952	8.29	380	2.55	19.5
Non-Domestic - GDP	0.988	0.976	8.29	768	2.55	27.7
Total - GDP	0.991	0.981	8.29	990	2.55	31.5

The correlation coefficient and hence the coefficient of determination for the Domestic and the Non-Domestic sectors and the Total consumption are very high. The lowest is for the Domestic-GDP case where r^2 is 0.952, implying that 95.2% of the variance in the Domestic consumption is explained by the current GDP values. Therefore, each consumption model coupled with a good forecast of current GDP should produce a good forecast for electricity consumption, as long as the relationship and the pertinent contextual factors remain essentially unchanged [Porter *et al.*, 1991]. The critical F-value for a 99% confidence level is 8.29 while the calculated value of F is much higher for all the three sectors, indicating that the relationship between electricity consumption and current GDP values are statistically significant. Similarly, the t-test values are much higher than the critical value of t at the 99% confidence level. This means that the hypothesis that the coefficient b' is zero can be rejected with much less than 1 percent probability of error.

Electricity Consumption versus Time

Having the models statistically validated, an equation combining consumption/GDP and GDP/time relationships can be derived. Equation 6.2 is rewritten in a more general form as

$$G = m + nt \tag{6.4}$$

Substituting Equation 6.4 into Equation 6.3 gives

$$Y = (a + bm) + bnt \tag{6.5}$$

This can be rewritten as

$$Y = a_0 + a_1 t \tag{6.6}$$

where,

Y is the electricity consumption in GWh,

$a_0 = a + bm$,

$a_1 = bn$, and

t is time in years.

Equation 6.6 can then be used as a model to forecast electricity consumption. A regression equation of the form of Equation 6.6 can be thought of as an abstract model that represents some aspect of reality [Makridakis and Wheelwright, 1989]. In the proposed model, it is assumed that future electricity consumption will be affected by GDP and the historical electricity consumption pattern. When electricity consumption is considered to be a function of time (as in the above model), reality is simplified and represented in terms of the interaction of two factors only [Makridakis and Wheelwright, 1989]. In reality, electricity consumption is also influenced by other factors such as population growth, pricing, electricity policy, amount of electricity using equipment, availability of fuel substitutes, growth in industry and efficiency of processes, etc. However, these influences are not investigated in this model.

The constants a_0 and a_1 for the Domestic, the Non-Domestic and the Total consumption are shown in Table 6.6. They are obtained using the regression constants *a, b, m* and *n* for each of the three sectors. Figure 6.15 shows the fitted Current GDP models for the Domestic and the Non-Domestic sectors and the Total consumption respectively.

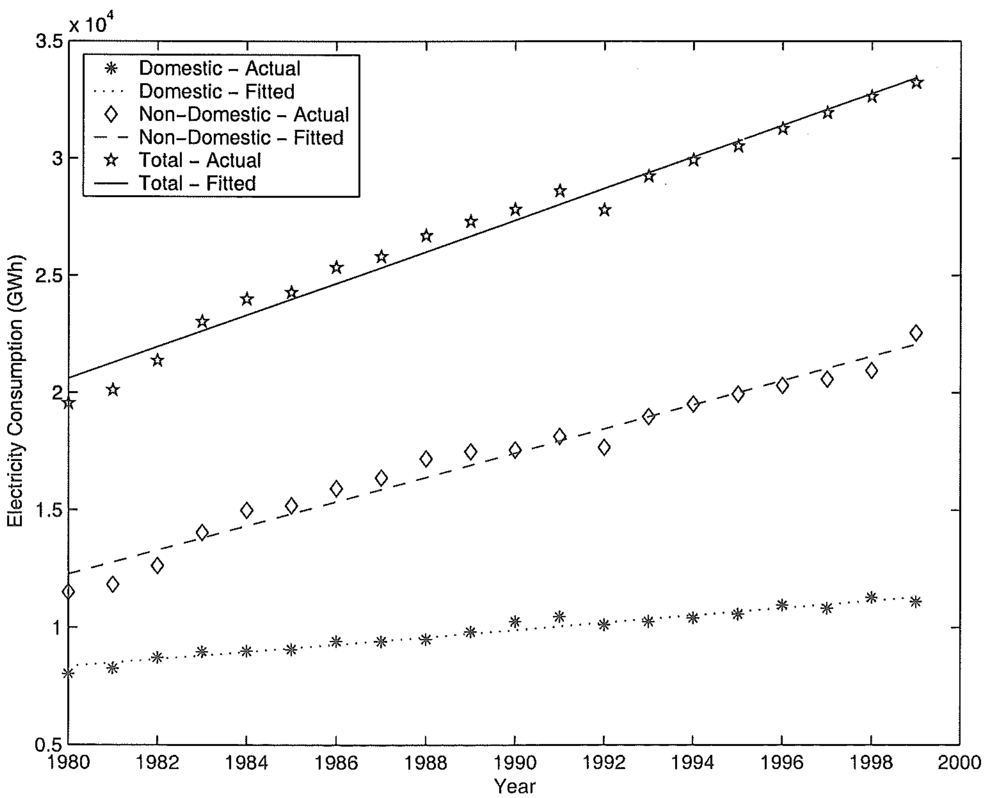

Figure 6.15 Fitted Current GDP models for electricity consumption in New Zealand

Table 6.6 Constant terms of the Current GDP models

Sector	a_0	a_1
Domestic	-2.99×10^5	155
Non-Domestic	-1.01×10^6	515
Total	-1.32×10^6	675

6.4.1.2 *Real GDP Model*

In the Real GDP model, the GDP values are referred to the constant 1991/92 New Zealand dollar prices. Figure 6.16 shows GDP at 1991/92 prices from 1963 to 1999 [Department of Statistics, 2000 & 2002] [Statistics New Zealand, 2002]. The real GDP values show a more linear trend than the current GDP even if the whole data set is selected. There is a period of slow or declined growth around the early 1990's. However an overall straight linear trend over the whole data set can be observed.

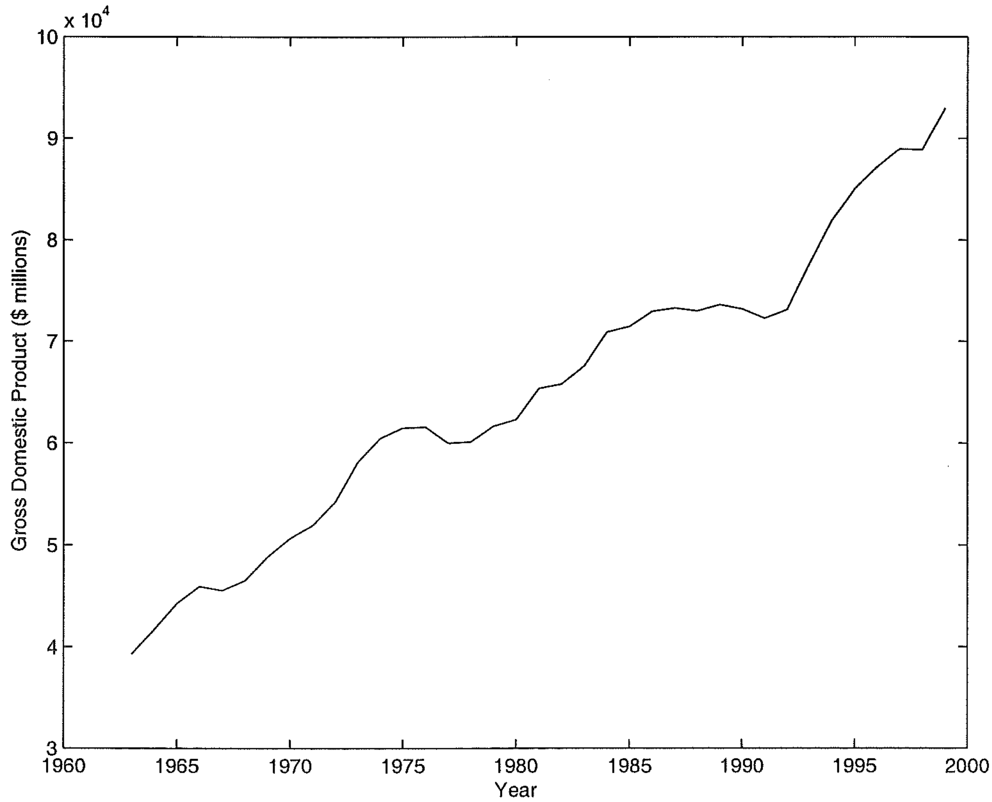

Figure 6.16 Real GDP at 1991/92 prices for New Zealand from 1963 to 1999

Figure 6.17 shows the total electricity consumption for the same period as the real GDP data.

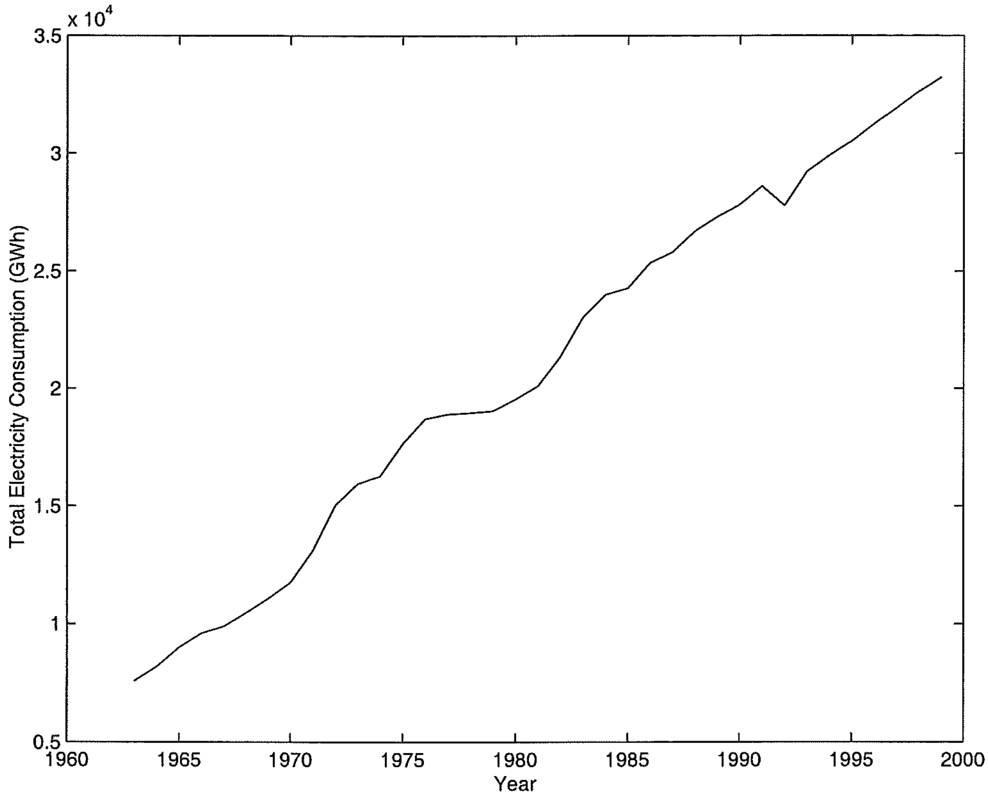

Figure 6.17 Total electricity consumption of New Zealand from 1963 to 1999

The two figures (Figure 6.16 and 6.17) show similar trends even though the smaller variations may not be coincident. However, both figures show a general increase until 1975, a slow or declined growth from 1975 to 1980, growth from the late 1980's to 1990 and then a decline in growth around 1992 before gaining growth again. The lower electricity consumption around 1992 is mainly due to the restrictions brought by the drought of 1992. These similarities suggest that there is a strong correlation between these two data sets, which may give rise to a reasonable linear model for electricity forecasting.

The Real GDP model is obtained initially for the period 1963 to 1999. However, since the Current GDP model is obtained for the period 1980 – 1999, a second model is proposed based on real GDP data from 1980 to 1999.

Real GDP Model 1963 – 1999

Figure 6.18 shows the real GDP values from 1963 to 1999 along with the fitted straight line using regression analysis.

The equation of the fitted line is

$$G = -2.53\times10^{6} + 1.31\times10^{3}t \qquad (6.7)$$

where,

G = GDP (NZ$ millions), and

t = time in years from 1963

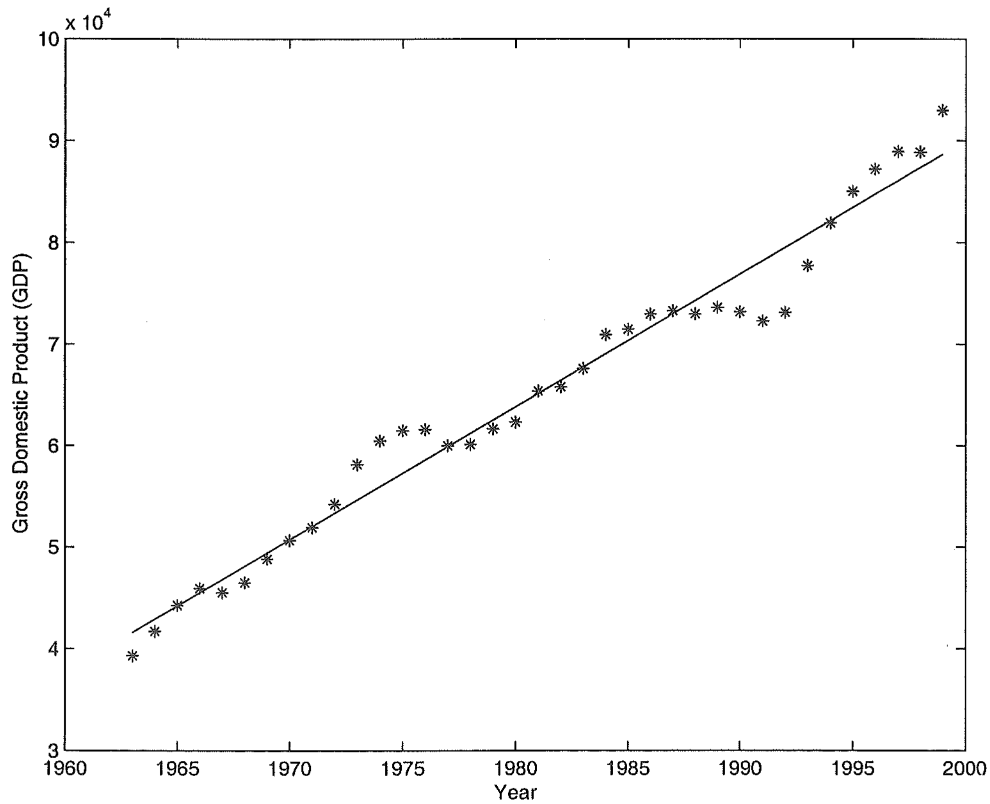

Figure 6.18 Real GDP with the best fit straight line

This is slightly a better fit than the straight line fit for current GDP. Figure 6.19 shows graphs of GDP and electricity consumptions for the Domestic and the Non-Domestic sectors and the Total electricity consumption along with the respective best fitted lines. Table 6.7 summarises the coefficients a and b of Equation 6.3.

Table 6.7 Coefficients of the fitted straight lines for real GDP versus electricity consumption (1963-99)

Sector	a	b
Domestic	-1.79×10^1	0.130
Non-Domestic	-1.43×10^4	0.410
Total	-1.79×10^2	0.091

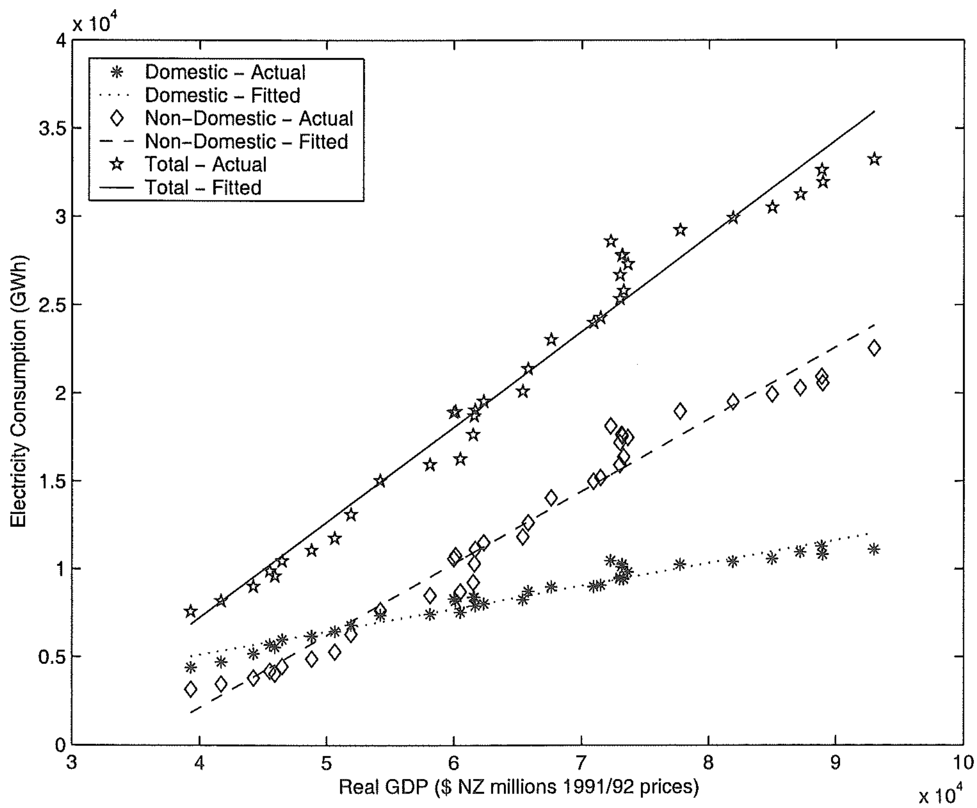

Figure 6.19 Electricity consumption against real GDP (1963-99) with the fitted straight lines

A validity test similar to that run for Current GDP model is presented in Table 6.8. The worst coefficient of determination is again for the Domestic-GDP sector, but it still implies that 95% of the variance in Domestic consumption is explained by the real GDP values. Therefore, each of these consumption models coupled with a good forecast of real GDP should produce a good forecast of electricity consumption. The critical F-value for 99% confidence level is 4.42 while the calculated value of F is much higher for all the three sectors indicating that the relationship between electricity consumption and current GDP values are statistically significant. Similarly the t-test values are much higher than the critical value of t at the 99% confidence level rejecting the hypothesis that the coefficient b' is zero with much less than 1 percent probability of error.

Table 6.8 Statistical results for real GDP and electricity consumption (1963 – 1999)

	Correlation coefficient	r^2	F-test		t-test	
			99% value	F	99% value	t
Domestic - GDP	0.974	0.949	7.42	37.03	2.44	6.08
Non-Domestic - GDP	0.983	0.983	7.42	56.79	2.44	7.54
Total - GDP	0.985	0.970	7.42	64.74	2.44	8.05

The constants a_0 and a_1 of the proposed model of Equation 6.6 for electricity consumption are shown in Table 6.9.

Table 6.9 Constants of the Real GDP model (1963-1999)

Model	a_0	a_1
Domestic	-3.29×10^5	170
Non-Domestic	-1.05×10^6	536
Total	-1.38×10^6	708

Figure 6.20 shows the fitted Real GDP models (1963 – 1999) for the Domestic and the Non-Domestic sectors and the Total electricity consumption respectively. The Real GDP models (1963-1999) have also produced very good fits to the historical data. However, as more historical data is used in this model and the variation in these early years are more significant, the fit in these years may be slightly worse than the Current GDP model. Therefore a Real GDP model has also been developed using the same amount data as the Current GDP model. This will facilitate a better comparison between these two models.

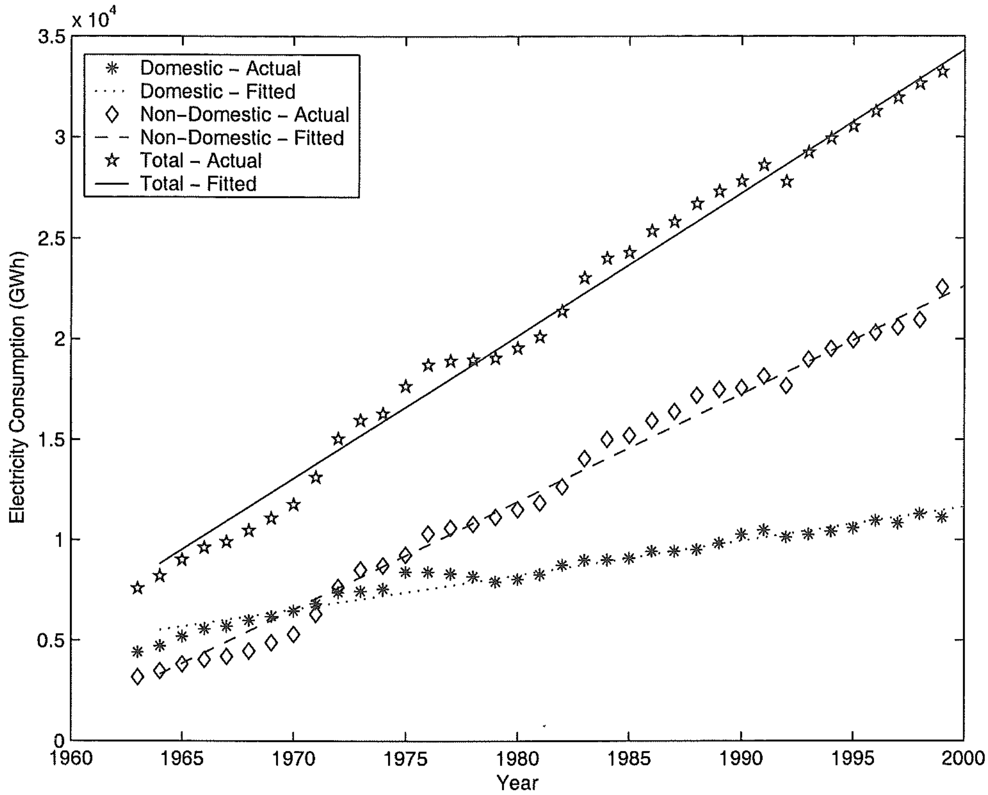

Figure 6.20 Fitted Real GDP model (1963-1999) for electricity consumption in New Zealand

Real GDP model 1980 – 1999

Similar analysis is carried out as for the Real GDP model (1963-1999), but using data for the period 1980 to 1999. Table 6.10 summarises the correlation coefficient, coefficient of determination and results for *F*-test and *t*-test along with the corresponding critical values.

Table 6.10 Statistical test results for the Real GDP model (1980-1999)

	Correlation coefficient	r^2	*F*- test 99% value	*F*	*t* -test 99% value	*t*
Domestic - GDP	0.909	0.826	8.29	90.2	2.55	9.50
Non-Domestic - GDP	0.943	0.888	8.29	151	2.55	12.3
Total - GDP	0.940	0.884	8.29	145	2.55	12.0

The correlation coefficients are lower than for the other two GDP models considered but are at acceptable levels. The model has also passed the F-test and t-test even at the 99% confidence level. The coefficients of the proposed model of Equation 6.6 are obtained in a similar fashion and are shown in Table 6.11.

Table 6.11 Coefficients of the Real GDP model (1980-1999)

Model	a_0	a_1
Domestic	-2.65×10^5	138
Non-Domestic	-9.19×10^5	470
Total	-1.19×10^6	614

Figure 6.21 shows the fitted Real GDP models (1980-1999) for the Domestic and the Non-Domestic sectors, and Total consumption respectively.

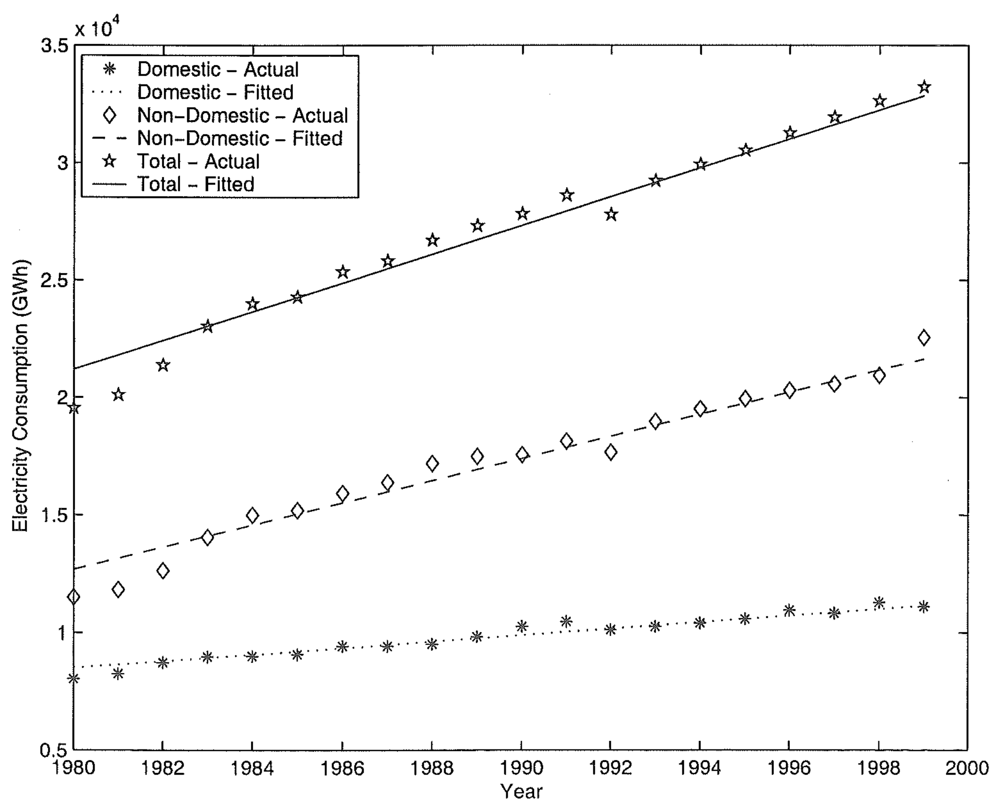

Figure 6.21 Fitted Real GDP models (1980-1999) for electricity consumption in New Zealand

These fits are very similar to the Current GDP model and the Real GDP model (1963 - 1999). This indicates a measure of stability in the model over the longer time periods.

6.4.2 Linear Model Based on Electricity Price

Electricity price is another crucial factor that may affect electricity consumption. Electricity prices for New Zealand were obtained from the Ministry of Economic Development [MED, 2002] [MED, 1958-74]. Prices are expressed in both real and current terms. Real prices are calculated using national deflators to illustrate price trends relative to inflation (See Appendix A for the actual data). However, observation of real prices over the years indicated that it has remained very much unchanged over the past 20 years and thus has resulted in a low correlation to electricity consumption. However, there is a strong correlation between current price and electricity consumption. Thus, current price is used in developing these models.

6.4.2.1 Current Price Model

Figure 6.22 shows the current price of electricity from 1960 to 1999. To be consistent with electricity consumption and GDP data, the price data for 1999 indicates the average price for the year ended March 2000. The price remained very much unchanged from 1960 to 1975. From 1975 onwards an increasing trend can be observed except for the last two years. Visual observation of the price data indicates that the price may be explained using a linear approximation. Since the previous GDP models are obtained using data from the years 1980 to 1999, the Current Price model also uses price data from 1980 to 1999. In addition, the correlation is stronger when this period is chosen. A statistically acceptable model cannot be developed if the whole data set is selected. Figure 6.23 shows the current price from 1980 to 1999 along with the fitted line.

The equation of the fitted line is

$$P = -627 + 0.319t \qquad (6.8)$$

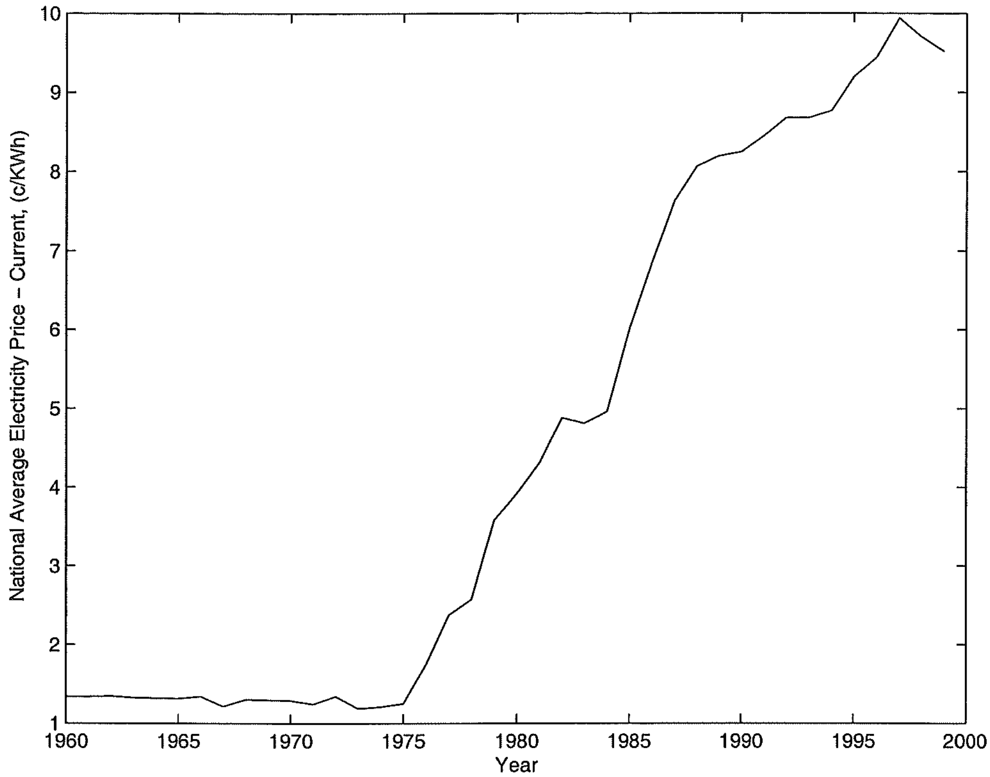

Figure 6.22 Current electricity prices in New Zealand from 1960 to 1999

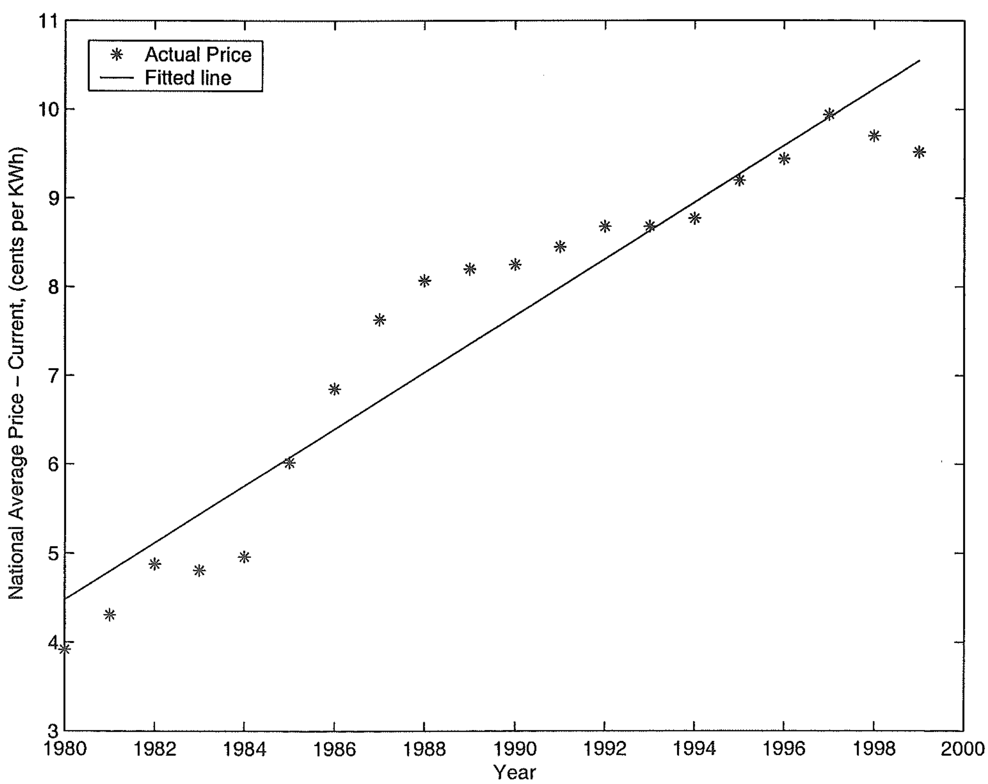

Figure 6.23 Current price from 1980 to 1999 along with the best fit straight line

where,

P is the current electricity price, and

t is time in years from 1980.

Figure 6.24 shows the current price versus electricity consumption for the Domestic and the Non-Domestic sectors, and the Total consumptions along with the best fit line for each data set.

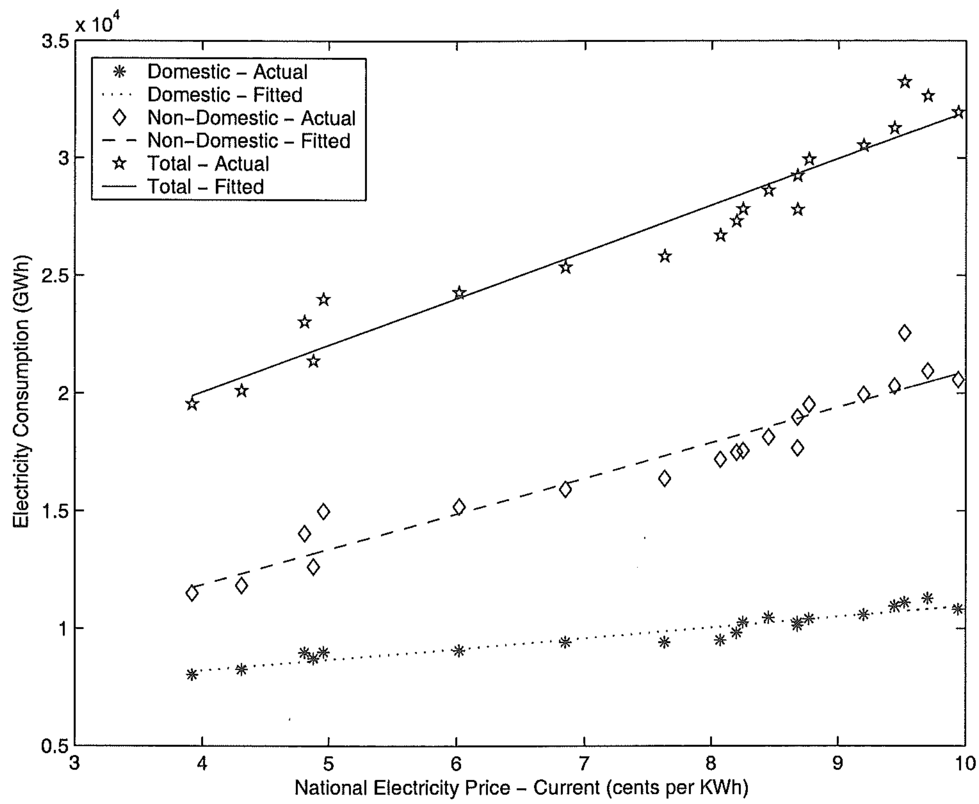

Figure 6.24 Electricity consumption against current electricity price with the best fit lines

The equation of the fitted line for each of the sectors is obtained by modifying Equation 6.3 to:

$$Y = a + bP \tag{6.9}$$

where,

Y is the electricity consumption in GWh,

a and b are coefficients shown in Table 6.12, and

P is the current price in cents per kWh.

Table 6.12 shows the coefficients of the fitted lines corresponding to Equation 6.9.

Table 6.12 Coefficients of the best fitted lines for price versus electricity consumption

	a	b
Domestic	6.39×10^3	4.58×10^2
Non-Domestic	5.84×10^3	1.51×10^3
Total	1.21×10^4	1.98×10^3

The correlation coefficients, the coefficients of determination, F-tests and t-tests results are shown in Table 6.13.

Table 6.13 Statistical test results for electricity price versus consumption

	Correlation coefficient	r^2	F-test 99% value	F-test F	t-test 99% value	t-test t
Domestic - Price	0.955	0.912	8.29	196	2.55	14.0
Non-Domestic - Price	0.958	0.918	8.29	213	2.55	14.6
Total - Price	0.964	0.930	8.29	252	2.55	15.9

The correlation coefficient and hence the coefficient of determination for the Domestic and the Non-Domestic sectors and the Total consumption are lower than for the GDP models but are still high, implying that even in the worst case, 91% of the variance in the Domestic consumption is explained by the electricity price. Therefore, each of these consumption models coupled with a good forecast of electricity price should produce a good forecast of electricity consumption. The critical F-value for a 99% confidence level is 8.29 while the calculated value of F is much higher for all three sectors, indicating that the relationship between electricity consumption and electricity prices are statistically significant. Similarly, the t-test values are much higher than the critical value of t at the 99% confidence level. This means the hypothesis that the coefficient b' is zero can be rejected with much less than 1 percent probability of error.

The fitted lines for electricity consumption using the Current Price model are obtained using the same procedure as for the GDP models. Thus, the constants a_0 and a_1 of Equation 6.6 are obtained by regression analysis for the price. Table 6.14 shows the constants of the fitted lines for the Current Price models.

Table 6.14 Coefficients of the Current Price models

Sector	a_0	a_1
Domestic	-2.81×10^5	146
Non-Domestic	-9.40×10^5	481
Total	-1.23×10^6	633

Figure 6.25 shows the fitted Current Price models for the Domestic and the Non-Domestic sectors and the Total electricity consumption respectively. It can be seen that these linear models using current electricity price have produced very acceptable fits and are very comparable with the GDP models.

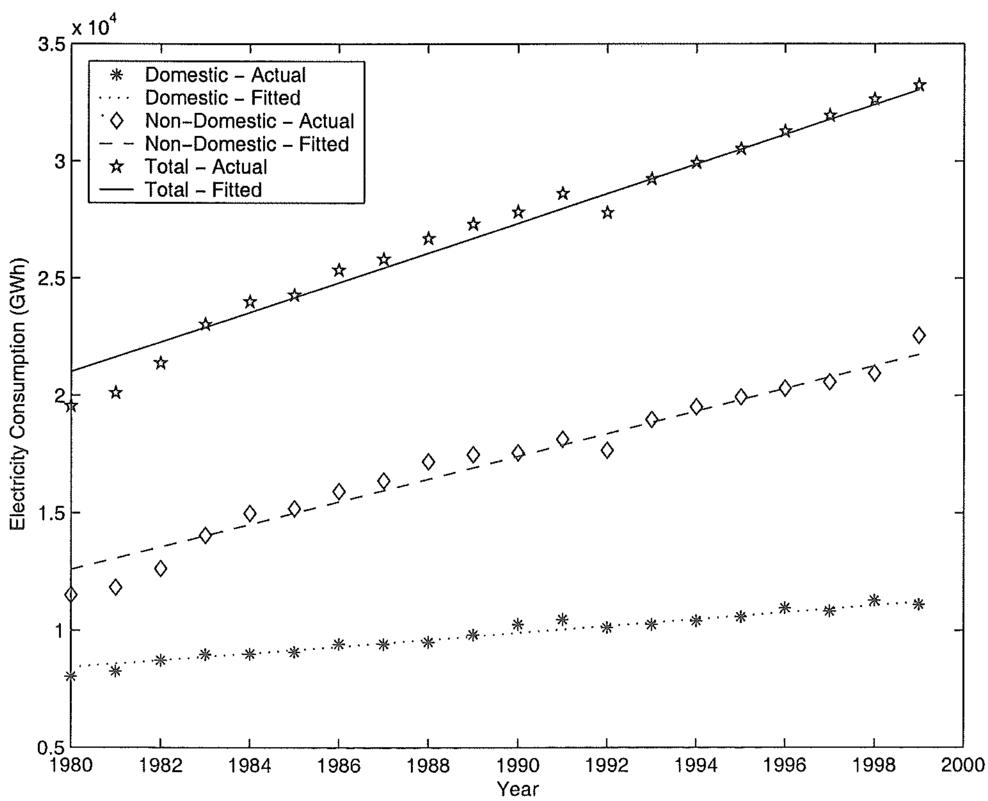

Figure 6.25 Fitted Current Price models for electricity consumption in New Zealand

6.4.3 Combined Model

In the previous two sections, independent simple linear models for forecasting electricity were proposed based on the strength of the relationship between electricity consumption and the independent variables. These models have also produced acceptable electricity consumption forecasts. A model dependent on a single independent variable may be too unstable as any changes in the pattern of that single variable will be directly reflected on the electricity consumption forecast. As discussed before, a number of forecasting models have been proposed using a combination of econometric and demographic variables rather than a single variable. Most commonly used variables in such studies are GDP, price of electricity and population. In addition, the analysis in Chapter 2 indicated that the link between GDP and population to electricity consumption is strong in many countries. It was decided not to use other variables to be consistent (for easy comparison) with the Combined models of other countries to be developed. Therefore, the Combined model[1] based on the dependency of electricity consumption on GDP, price and population using multiple regression analysis is proposed for New Zealand [Mohamed and Bodger_1, 2004]. The addition of electricity price for New Zealand added more stability to the Combined model. Therefore it was added in the Combined model of New Zealand.

The proposed Combined model for New Zealand is

$$Y = a + b_1 X_1 + b_2 X_2 + b_3 X_3 + u \tag{6.10}$$

where,

Y is the electricity consumption (GWh),

X_1 is GDP ($NZ millions),

X_2 is electricity price (cents/ kWh),

X_3 is population, and

u is the error (*disturbance term* or *white noise*).

---

[1] The works on electricity forecasting in New Zealand using the Combined model has been accepted for publication in *Energy, The International Journal* [Mohamed and Bodger_1, 2004].

In order to make forecasts, each of the independent variables X_1, X_2 and X_3 are themselves obtained from simple linear regression applied to data sets of these variables over time (t).

$$\begin{aligned} X_1 &= c_{01} + c_{11}t \\ X_2 &= c_{02} + c_{12}t \\ X_3 &= c_{03} + c_{13}t \end{aligned} \tag{6.11}$$

where, c_{01}, c_{11}, c_{02}, c_{12}, c_{03} and c_{13} are the constants of the respective simple linear regressions.

The GDP data used in the Combined model are in constant 1991/92 \$NZ. However, electricity price data used in this model are in current \$NZ. Attempts to use constant electricity prices instead of the current electricity prices degraded the performance of the models. As for the linear models, the total electricity consumption data is divided into the Domestic and the Non-Domestic sectors. The Combined models are proposed for New Zealand using all data from 1965 to1999. The models are also validated using the same statistical tests as for the simple linear models. In addition, the residual plots of the error, *u,* is also studied to determine the appropriateness of the model as they are commonly used in multiple linear regression models [Egelioglu *et al.*, 2001].

The dependency of each of these variables on one another is shown by the respective correlation coefficients. Table 6.15 shows the correlation matrix for the variables used in the multiple linear regression analysis for modelling New Zealand data from 1965 – 1999. All the independent variables are highly correlated to the dependent variables (Domestic, Non-Domestic and Total consumption) and therefore are significant in their use in the forecasting model. The correlation coefficient for GDP vs. Population is 0.982. It may appear that multicollinearity exists in this situation. Multicollinearity is first and foremost a computational problem [Makridakis *et al.*, 1998]. That is, if perfect multicollinearity exists in a regression problem then it is not simply possible to carry out a least squares solution. The program developed for the Combined model performed effectively for the given data. Attempting to discard population or GDP did not produce a better model. Therefore, it was decided to include these three variables in the model.

Table 6.15 Correlation matrix for variables used in the Combined model

	Domestic	Non-Domestic	Total	GDP	Price	Population
Domestic	1			0.971	0.921	0.983
Non-Domestic		1		0.981	0.963	0.980
Total			1	0.982	0.956	0.984
GDP				1	0.928	0.982
Price					1	0.922
Population						1

The coefficients a, b_1, b_2 and b_3 (Equation 6.10) for each of the Domestic and the Non-Domestic sectors and the Total consumption are obtained by multiple linear regression using 35 years of data from 1965-1999 for each of the variables. The resulting Combined models are:

For Domestic:

$$Y_1 = -5.81\times10^3 + 1.5\times10^{-3} X_1 - 93.2 X_2 + 4.7\times10^{-3} X_3 \tag{6.12}$$

For Non-Domestic:

$$Y_2 = -2.98\times10^4 + 2.29\times10^{-1} X_1 + 78.7 X_2 + 8.2\times10^{-2} X_3 \tag{6.13}$$

For Total consumption:

$$Y_3 = -3.68\times10^4 + 2.21\times10^{-1} X_1 - 2.10 X_2 + 1.34\times10^{-2} X_3 \tag{6.14}$$

The independent variables GDP (X_1), price (X_2) and population (X_3) are estimated using simple linear regression. The resulting equations for the forecasts of X_1, X_2 and X_3 are

$$X_1 = -2.49\times10^6 + 1.29\times10^3 t \tag{6.15}$$

$$X_2 = -267 - 0.130t \tag{6.16}$$

$$X_3 = -5.91\times10^7 + 3.15t \tag{6.17}$$

where, t is the time in years from 1965.

Table 6.16 shows the validity test results for the Combined models. The adjusted coefficient of determination, calculated F and t values along with the 99% critical values are given. For the F statistics the number of degrees of freedom of the numerator is 3 and the number of degrees of freedom for the denominator is 32. For the t statistics the number of degrees of freedom is 32.

Table 6.16 Validity test results for the Combined models

Model	Adjusted r^2	F- test		t-test			
		99% critical F	F	99% critical t	t_1	t_2	t_3
Domestic	0.89	4.46	258	2.74	4.04	3.19	30.0
Non-Domestic	0.96	4.46	1077	2.74	17.3	21.6	21.1
Total	0.96	4.46	1024	2.74	10.2	17.8	30.4

The Domestic consumption model developed is good with adjusted r^2 of 0.89, but better models may exist as the adjusted r^2 is less than 0.9. During the early 1970's domestic electricity consumption in New Zealand grew rapidly mainly due to the conversion to electric space heating, the near universal use of electric water heating, and the widespread use of appliances such as washing machines and television sets [Ministry of Energy, 1982-84]. However, during the late 1970's the electricity consumption dropped noticeably due to a downturn in the economy combined with high electricity prices [Ministry of Energy, 1982-84]. Coal and natural gas attracted some of this demand. The increase in domestic electricity consumption in the early 1970's (especially the gap between 1974 and 1975) and the decrease in domestic electricity consumption between 1975 and 1979 may have resulted in the low adjusted r^2 in the Domestic model compared to the other two models.

The adjusted coefficient of determination for the Domestic and the Non-Domestic sectors and the Total consumption are high implying that even in the worst case of the Domestic sector 89% of the variance in consumption is explained by the combination of GDP, price and population data. Therefore, each of these consumption models coupled with a good forecast of electricity price, GDP and population should produce good forecasts of electricity consumption. The critical value of F for each of the sectors is much smaller than the calculated F value. Therefore, it can be concluded that the Combined models are significant even at the 99% confidence level. Similarly, the t- test results t_1, t_2 and t_3, for the coefficients of X_1, X_2 and X_3, are higher than the 99% critical value of t. This means that each of these coefficients b_1, b_2 and b_3 (Equations 6.12 to 6.14) are significant in their use in the models.

Figure 6.26 shows the actual electricity consumption along with the estimated values using the Combined models developed. As can be seen, appropriate fits of the historical data are provided by these models.

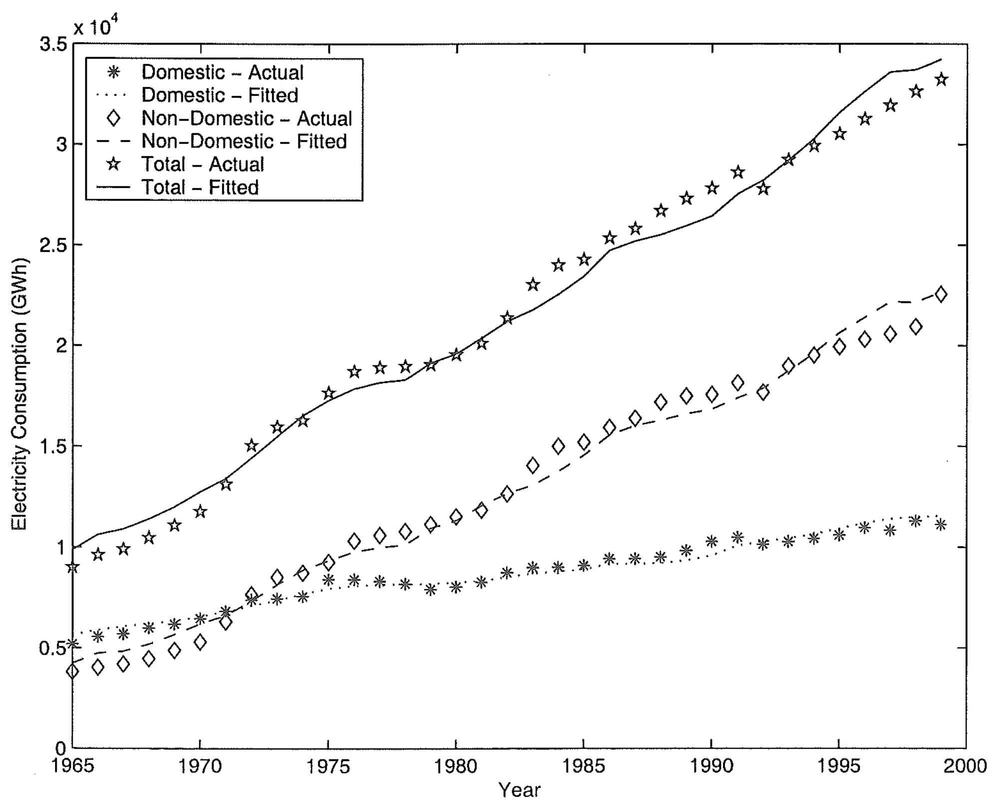

Figure 6.26 Fitted Combined models for electricity consumption in New Zealand

The residuals produced by these models are also well behaved. Figure 6.27 shows the residuals produced by the Total consumption model for the three independent variables and the fitted values. The plots are scattered in a horizontal band with no value too far from the band and no patterns such as curvature or increasing spread. Thus, the residuals are deemed to behave randomly and no other explaining variable is required. It seems that there is a relation between residual and price of electricity but this may be due to relatively constant electricity prices between 1965 and 1975 (see Figure 6.22).

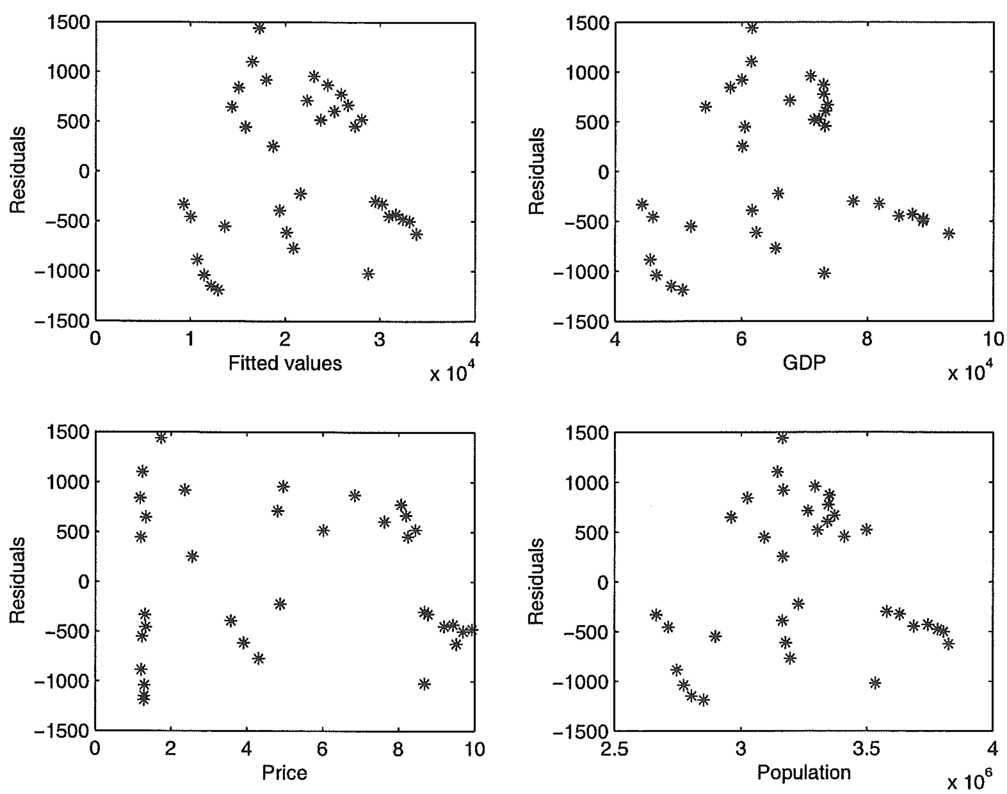

Figure 6.27 Plots of residuals against fitted values, GDP, price and population for total consumption

6.4.4 Comparison of the Econometric Models

Comparisons of the fits by the econometric models for New Zealand are presented. The mean square errors (MSE) of the fitted models are shown in Table 6.17. For the purpose of this comparison all models are developed using data from 1980 to 1999. The Combined models for both the sectors and the Total consumption have produced much better fits than the other simple linear models. In many situations the best model is chosen based on how good the model fits the historical data. Young [Young, 1993] states that recent studies [Fildes and Howell, 1979] [Fildes, 1983] [Makridakis *et al.*, 1984] have raised the issue that the best model fit does not always provide the best forecasting model. Often, there is the issue that more complex models do not give better forecasts than the very simple models. This issue will be discussed in Chapter 11.

Table 6.17 Comparison of model fits for the econometric models proposed for New Zealand

Model	Mean square error (MSE)		
	Domestic	Non-Domestic	Total
Real GDP	4.52×10^4	3.56×10^5	4.83×10^5
Current GDP	3.35×10^4	2.82×10^5	3.37×10^5
Current Price	3.74×10^4	3.26×10^5	4.09×10^5
Combined	1.91×10^4	1.35×10^5	1.68×10^5

The Combined model not only provided better fits of the historical data but allowed more flexibility as changes in more than one explaining variables is incorporated in that model. In addition, models similar to the Combined models have been used more often in electricity forecasting. Thus, only the Combined model is chosen from the econometric models and applied to other countries and regions of the world for forecasting and comparison with other models.

6.5 ARIMA MODELS

The ARIMA modelling technique is applied to the annual electricity consumption data of New Zealand from 1943–1999 [Ministry of Energy, 1982-84] [MED, 2002]. Thus ARIMA models are obtained for the Domestic and the Non-Domestic sectors and the Total electricity consumption. The software package ITSM 2000 [Brockwell and Davis, 2002] is used as an aid in the calculations.

6.5.1 Domestic ARIMA Model

The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the Domestic electricity consumption in New Zealand are shown in Figure 6.28.

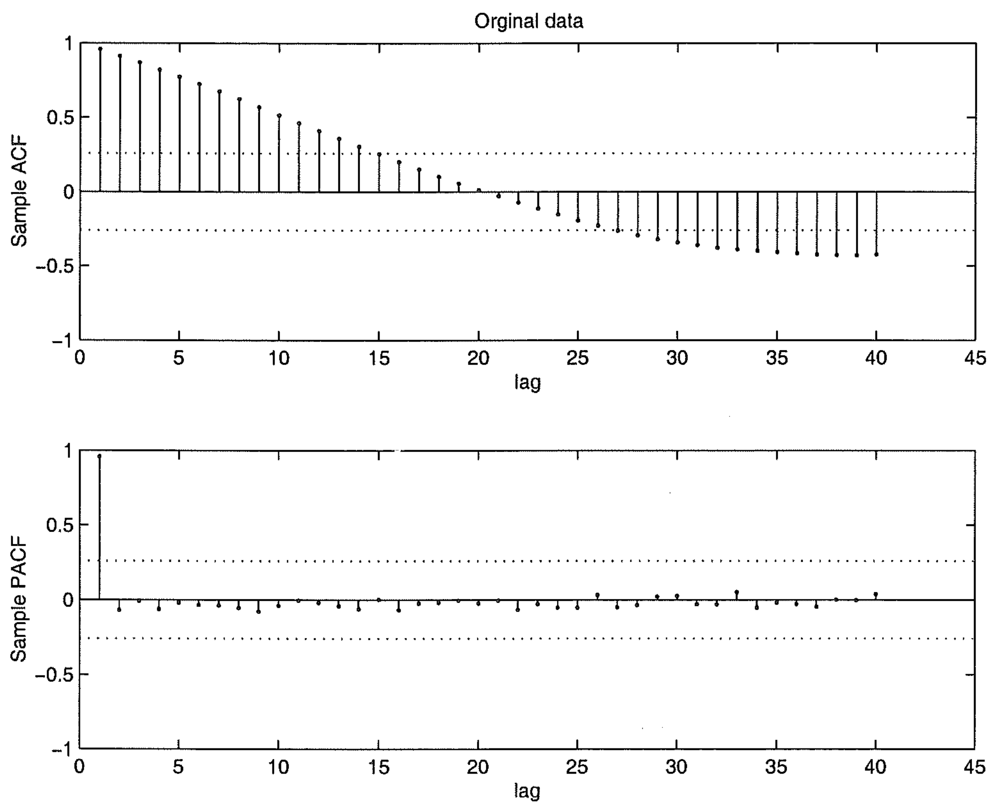

Figure 6.28 ACF and PACF of the original Domestic electricity consumption data

The $\pm 1.96/\sqrt{n}$ bounds for the ACF and PACF are shown by the dotted lines. A significant amount of autocorrelations are outside the limits indicating that the Domestic electricity consumption is not stationary. The first partial autocorrelation coefficient is very dominant and close to 1, also indicating non-stationarity. Therefore the data is differenced at lag 1. The results are shown in Figure 6.29. Now the ACF and PACF both indicate that the series is stationary with all coefficients except one within the required bounds. There is no significant ACF or PACF coefficient at lower lags. This suggests that an ARIMA(0,1,0) model could be appropriate to describe the data.

It is good practice to try out all other models that are similar to the model suggested by the ACF and PACF. Table 6.18 shows the AICC values of the ARIMA(0,1,0) model and all models in the neighbourhood of this model up to ARIMA(2,1,2). Higher order models, which are not shown in the table, were also tried but failed to perform better. According to Table 6.18, the best model is the ARIMA (0,1,0) model with the lowest AICC value.

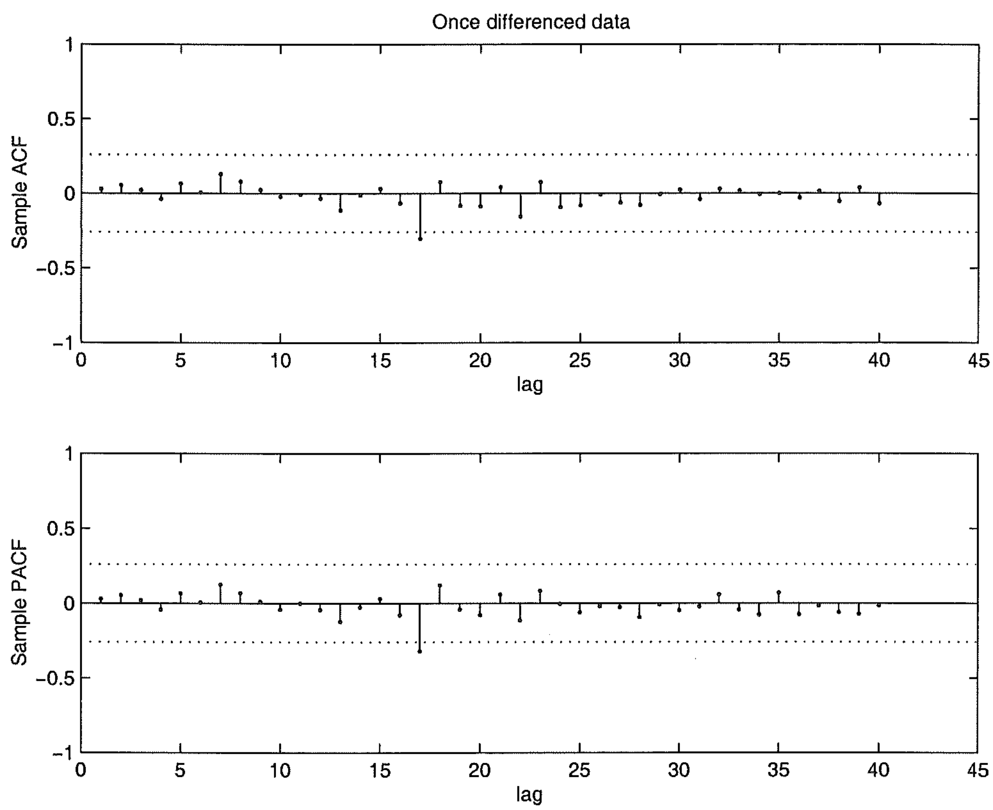

Figure 6.29 ACF and PACF of the first difference of the Domestic data

Since the order of p and q in this model is zero, the maximum likelihood estimation of the model is:

$$Y_t' = e_t \tag{6.18}$$

where e_t is approximated by a zero mean white noise (WN) sequence, i.e. $e_t \sim$ WN(0, 45000).

Since the data is differenced and mean corrected before estimation, $Y_t' = Y_t - Y_{t-1} - 182$ and thus

$$Y_t = Y_{t-1} + 182 + e_t \tag{6.19}$$

The fitted ARIMA(0,1,0) model for the historical Domestic data is shown in Figure 6.30.

Table 6.18 ARIMA models and the corresponding AICC values for Domestic sector

Model	AICC
ARIMA(0,1,0)	761.0
ARIMA(0,1,1)	763.1
ARIMA(0,1,2)	765.3
ARIMA(1,1,0)	763.1
ARIMA(1,1,1)	765.3
ARIMA(1,1,2)	767.7
ARIMA(2,1,0)	765.3
ARIMA(2,1,1)	767.7
ARIMA(2,1,2)	770.1

The fitted values have a MSE of 4.497×10^4. The ARIMA(0,1,0) has produced very good fits of the historical data. However, the model could only be accepted if it has satisfied the required diagnostic tests. Figure 6.31 shows the ACF and PACF plots of the residuals produced by the fitted model. It can be seen that the ACF and PACF values are within the bounds of $\pm 1.96/\sqrt{n}$ more than 95% of the time. Therefore, the residual series is white noise.

The results of the Ljung-Box statistic Q for lags h = 20 is 13.17 compared with the corresponding χ^2 distribution of 31.41. The value of Q = 13.17 is much lower than the chi-square value of 31.41. This indicates that the correlations are not significant and therefore it can be concluded that the data is white noise. Therefore, the selected model to forecast the Domestic electricity consumption in New Zealand is ARIMA(0,1,0).

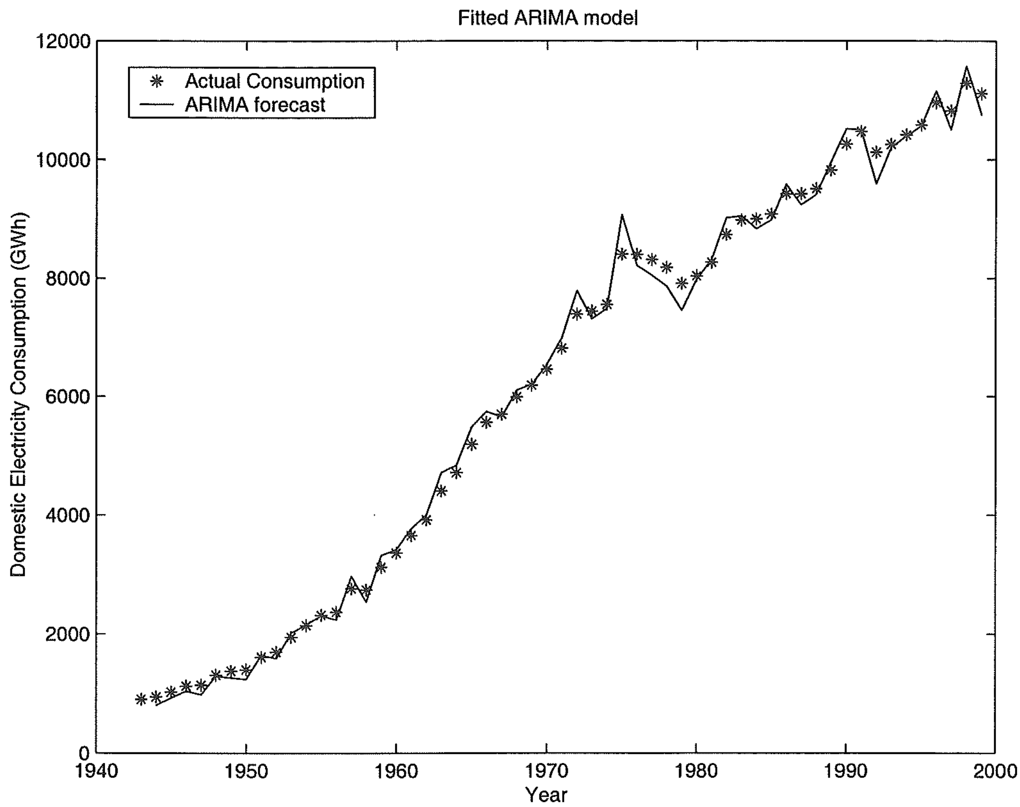

Figure 6.30 Fitted ARIMA(0,1,0) model for the Domestic electricity consumption

6.5.2 Non-Domestic ARIMA Model

The ACF and PACF plots for the original Non-Domestic electricity consumption data for New Zealand are shown in Figure 6.32. The ACF and PACF plots are very similar to those for the Domestic consumption data. A large amount of autocorrelations are outside the required bounds, shown by the dotted lines, indicating that the series is not stationary. As for the Domestic sector, the first partial autocorrelation coefficient is very dominant and close to 1, indicating a non-stationary process. Therefore, the first difference of the data is analysed. Figure 6.33 shows the corresponding ACF and PACF plots of the first differenced data. The plots still show that some correlations lie outside the limits indicating that the series needs to be differenced further. The ACF and PACF plots of the second differenced Non-Domestic data are shown in Figure 6.34.

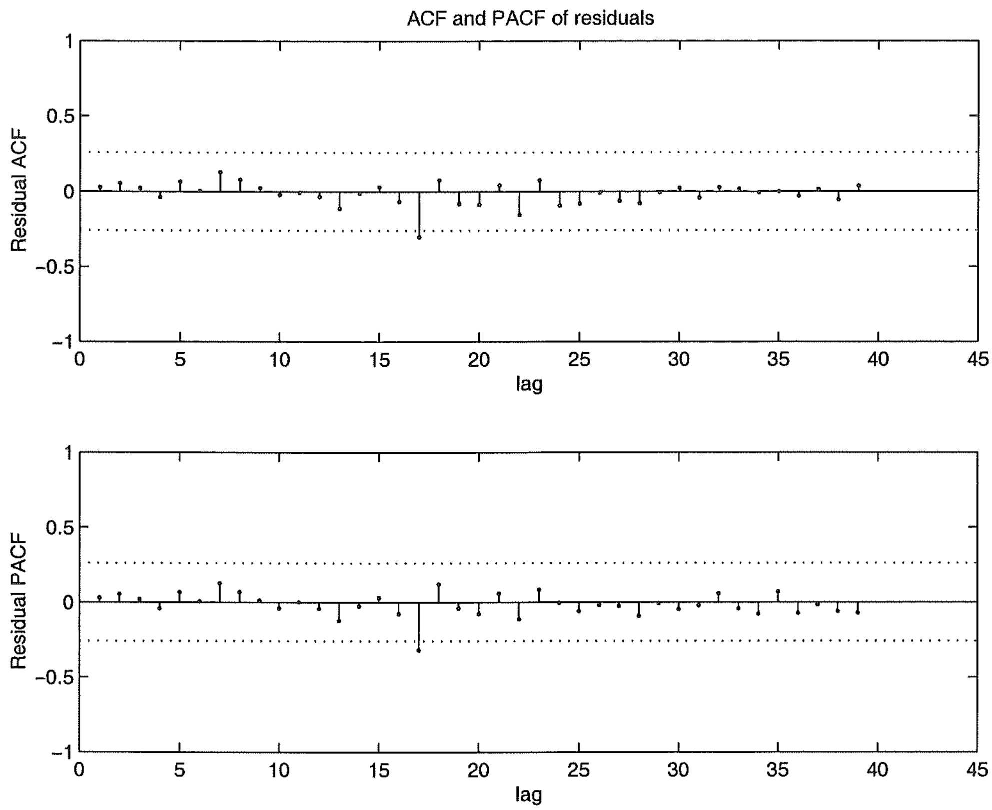

Figure 6.31 ACF and PACF of the residuals produced by ARIMA(0,1,0) for the Domestic sector

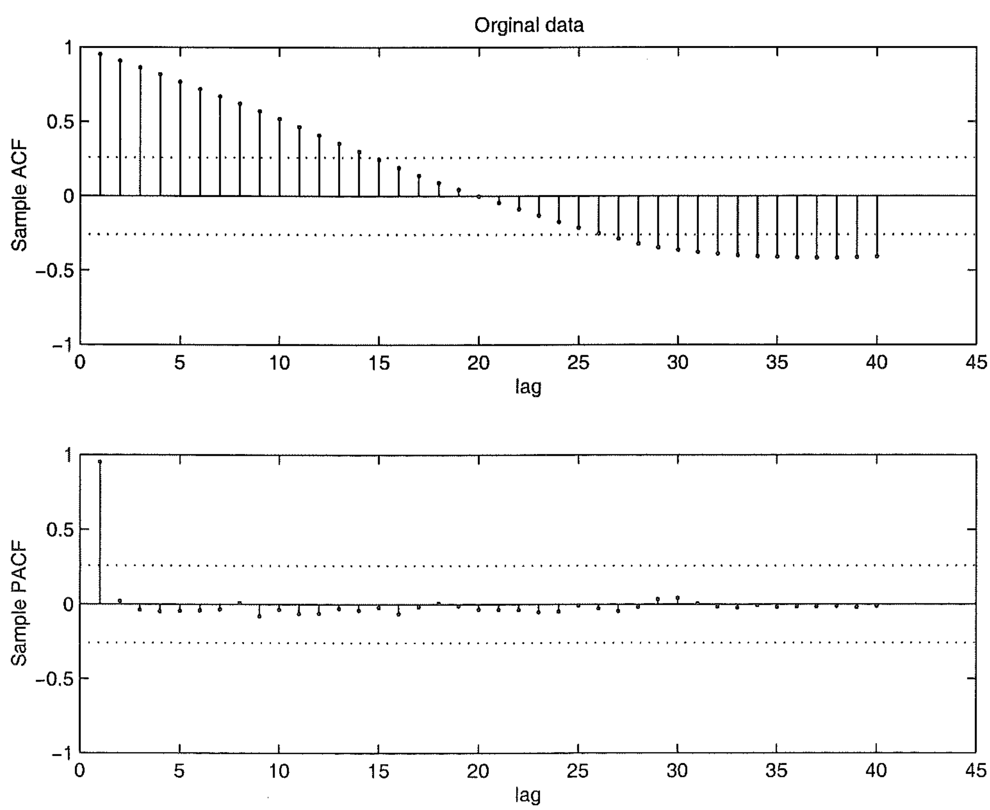

Figure 6.32 ACF and PACF plots of the original Non-Domestic consumption

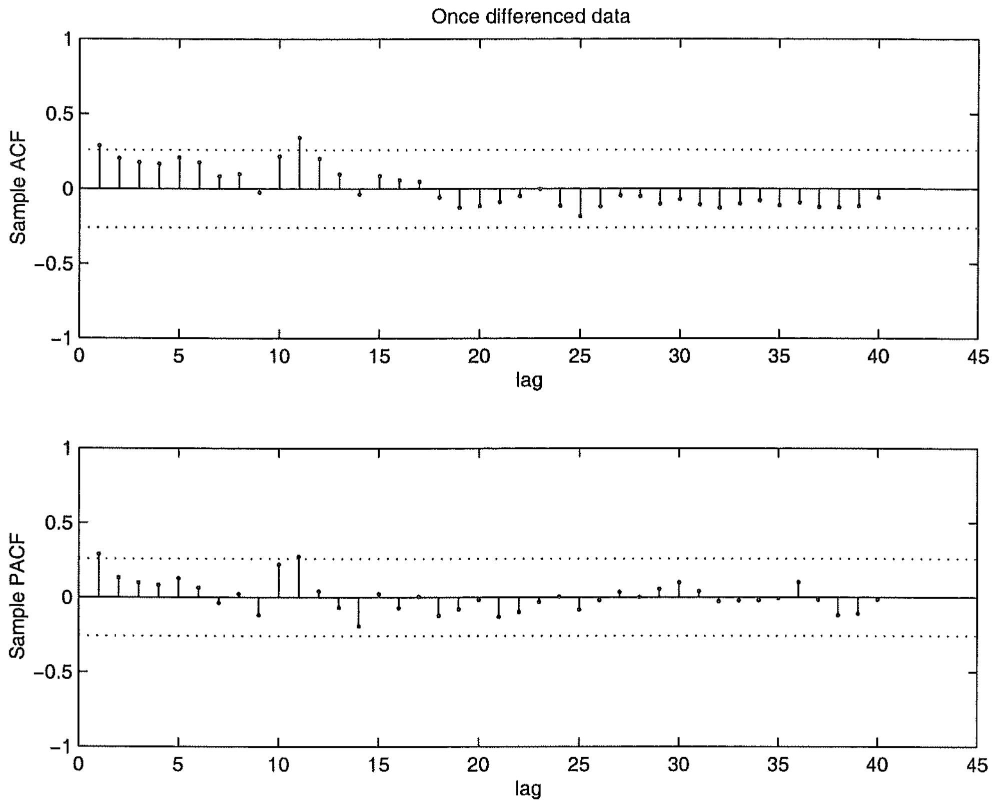

Figure 6.33 ACF and PACF plots of the first differenced Non-Domestic data

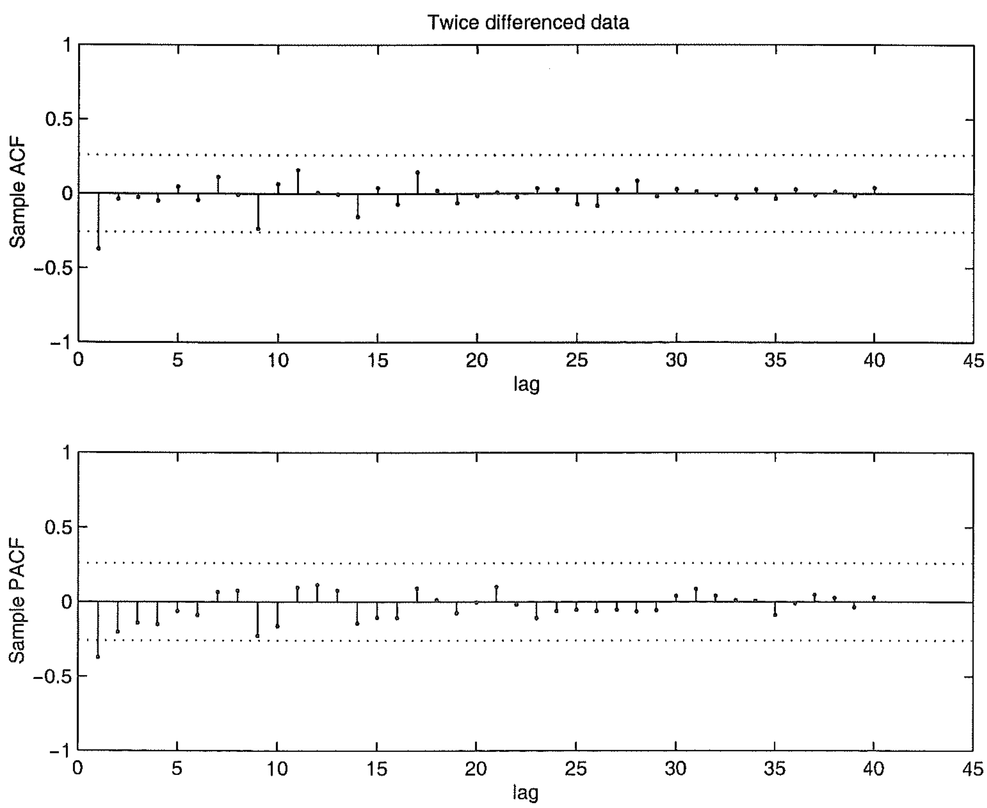

Figure 6.34 ACF and PACF plots of the two times differenced Non-Domestic data

Figure 6.34 shows that taking the second difference has significantly reduced the autocorrelation and partial autocorrelation coefficients, allowing them to be within the specified limits for stationary. The series is now stationary. The PACF shows a mixture of exponential decay and damped sine-wave. The ACF has one significant correlation at lag 1 indicating a possible ARIMA(0,2,1) model.

The identified model along with other possible models are investigated using AICC values as shown in Table 6.19. According to the AICC statistics, the identified ARIMA(0,2,1) with the lowest AICC value is the best model for the data.

Table 6.19 ARIMA models and the corresponding AICC values for the Non-Domestic sector

Model	AICC
ARIMA(0,2,0)	830.0
ARIMA(0,2,1)	813.1
ARIMA(0,2,2)	815.0
ARIMA(1,2,0)	822.8
ARIMA(1,2,1)	815.0
ARIMA(1,2,2)	817.3
ARIMA(2,2,0)	821.3
ARIMA(2,2,1)	817.3
ARIMA(2,2,2)	819.7

The estimated ARIMA(0,2,1) model is

$$Y_t'' = e_t - 0.778 e_{t-1} \tag{6.20}$$

where, $e_t \sim \mathrm{WN}(0,\ 1.40\times10^5)$.

Using Equation 4.42 and the subtracted mean before estimation, this can be re-written as

$$Y'' = Y_t - 2Y_{t-1} + Y_{t-2} - 28.9 \tag{6.21}$$

Substituting Equation 6.21 into Equation 6.20 gives the proposed ARIMA model as

$$Y_t = 2Y_{t-1} - Y_{t-2} + 28.9 + e_t - 0.778e_{t-1} \tag{6.22}$$

The fit of the Non-Domestic consumption given by the ARIMA(0,2,1) model is shown in Figure 6.35.

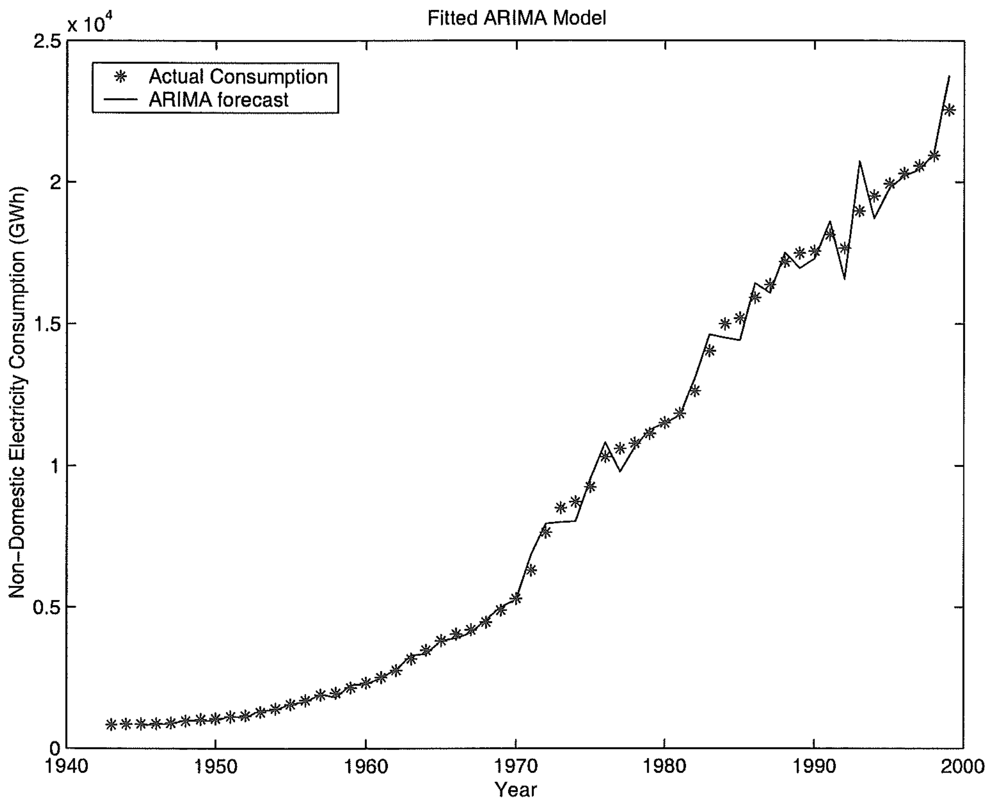

Figure 6.35 ARIMA(0,2,1) model fit for the Non-Domestic sector

It can be seen that the ARIMA (0,2,1) has produced a good fit of the historical Non-Domestic data. The MSE of the fitted model is 2.018×10^5. Figure 6.36 shows the ACF and PACF plots of the residuals produced by the fitted model. These plots show that almost all the autocorrelation and partial autocorrelation coefficients are small and are within the required bounds. This indicates that the residuals are white noise.

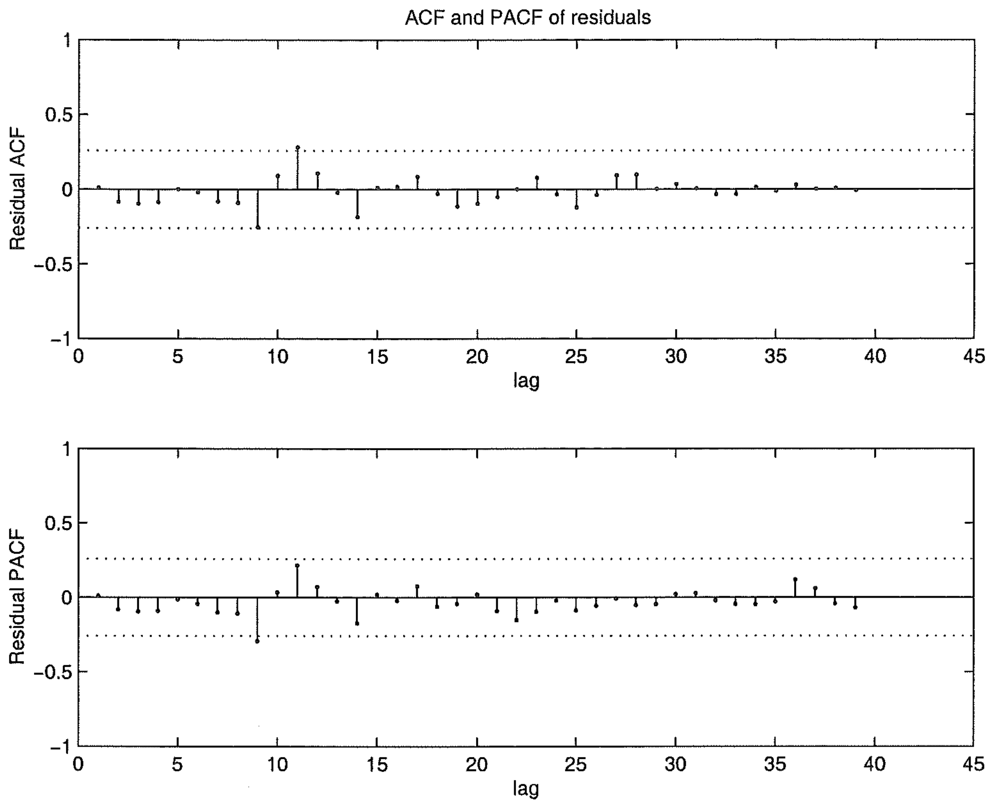

Figure 6.36 ACF and PACF of the residuals produced by the fitted ARIMA(0,2,1) model for the Non-Domestic sector

In addition, the Ljung-Box statistic, Q, is also calculated. The result for h = 20 lags is 19.25 compared with the corresponding chi-square (χ^2) value of 31.41. The value of Q = 19.25 is much lower than the chi-square value of 31.41. This strongly suggests that the correlations are not significant and the residuals are white noise. These diagnostic checks support the use of the ARIMA(0,2,1) model to forecast the Non-Domestic electricity consumption data.

6.5.3 ARIMA Model for Total Consumption

The Total electricity consumption is the sum of the annual Domestic and Non-Domestic consumption. The ACF and PACF of the original Total electricity consumption data is shown in Figure 6.37. The ACF and PACF plots are very similar to the plots of Domestic and Non-Domestic data. A significant amount of autocorrelations are outside the required $\pm 1.96/\sqrt{n}$ bounds. The first partial autocorrelation is very dominant with a value very close to 1. This indicates that the data is not stationary. The ACF and PACF plots of the first difference of the data are shown in Figure 6.38.

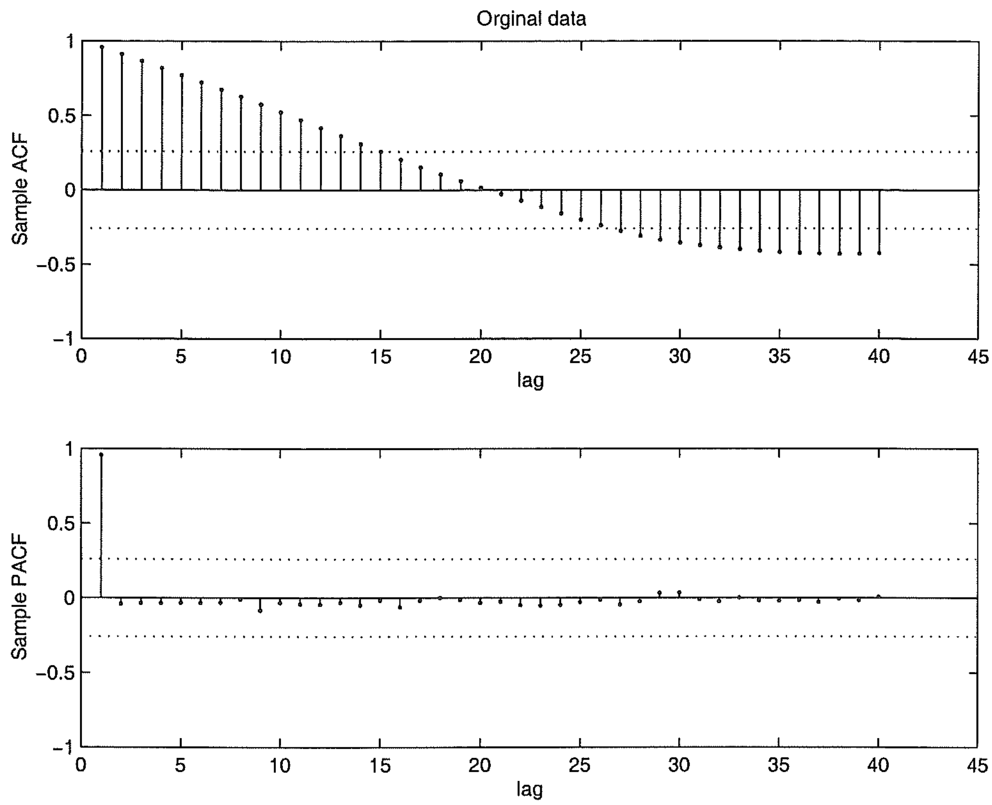

Figure 6.37 ACF and PACF of the original Total electricity consumption data

Now the autocorrelations and partial autocorrelations show a mixture of exponential decay and damped sine-wave pattern. The coefficients are generally within the required bounds indicating that the series is stationary. Significant ACF or PACF values are not present at lower lags to suggest a clear tentative model. However, the first ACF and PACF values are very much closer to the boundaries. This suggests that either an ARIMA(1,1,0), ARIMA(0,1,1) or ARIMA(1,1,1) model may be the best to describe the data. These models along with other similar models and their AICC values are shown in Table 6.20. The AICC values of the ARIMA(1,1,0) and ARIMA(1,1,1) are very close. However, the ARIMA(1,1,0) has the lowest AICC value. Thus, based on the AICC criteria the ARIMA(1,1,0) model is selected. The maximum likelihood estimation for the mean corrected model is

$$Y_t' = 0.279Y_{t-1} + e_t \qquad (6.23)$$

where, $e_t \sim$ WN(0, 1.97×10^5) is the zero mean white noise sequence.

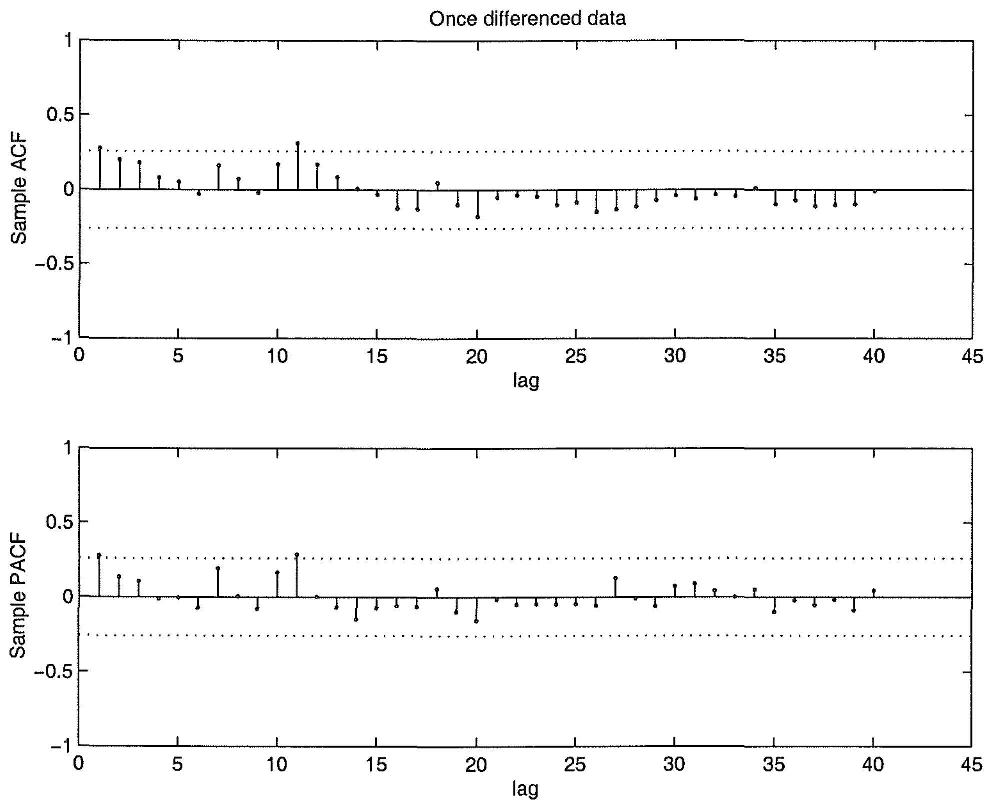

Figure 6.38 ACF and PACF of first differenced Total consumption data

Table 6.20 ARIMA models and the corresponding AICC values for the Total consumption

Model	AICC
ARIMA(0,1,0)	848.4
ARIMA(0,1,1)	847.0
ARIMA(0,1,2)	848.2
ARIMA(1,1,0)	846.0
ARIMA(1,1,1)	846.5
ARIMA(1,1,2)	848.7
ARIMA(2,1,0)	847.1
ARIMA(2,1,1)	848.7
ARIMA(2,1,2)	851.0

Substituting $Y_t' = Y_t - Y_{t-1} - 562$, in a similar way as for the Domestic and the Non-Domestic sectors, the model for Y_t is

$$Y_t = 1.279Y_{t-1} + 562 + e_t \tag{6.24}$$

The fit of the ARIMA(1,1,0) for the Total electricity consumption is shown in Figure 6.39.

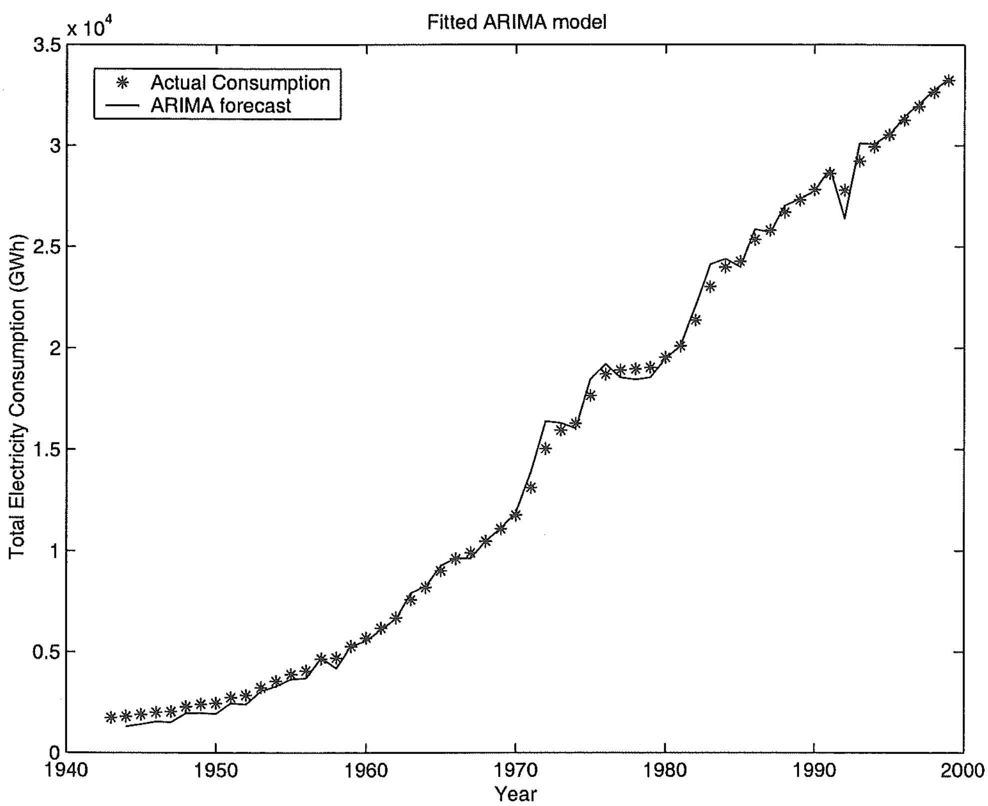

Figure 6.39 ARIMA(1,1,0) model fit for the Total electricity consumption

As for the Domestic and the Non-Domestic sectors, the Total consumption is quite accurately estimated by the selected ARIMA model. The MSE of this fitted model is 2.14×10^5. At this stage, the model is tested for the behaviour of the residuals. Figure 6.40 shows the residual ACF and PACF of the fitted ARIMA(1,1,0) model. Almost all the coefficients are within the required bounds indicating that the series is white noise. The results of the Ljung-Box Q statistic (for $h = 20$) is 18.13. The calculated Q value of 18.13 is much lower than the critical chi-squared value of 31.41 at the 95% probability level. This suggests that the correlations are not significant. Therefore, it can be concluded that the residuals are white noise. Hence, the ARIMA(1,1,0) model is used to forecast the Total electricity consumption of New Zealand.

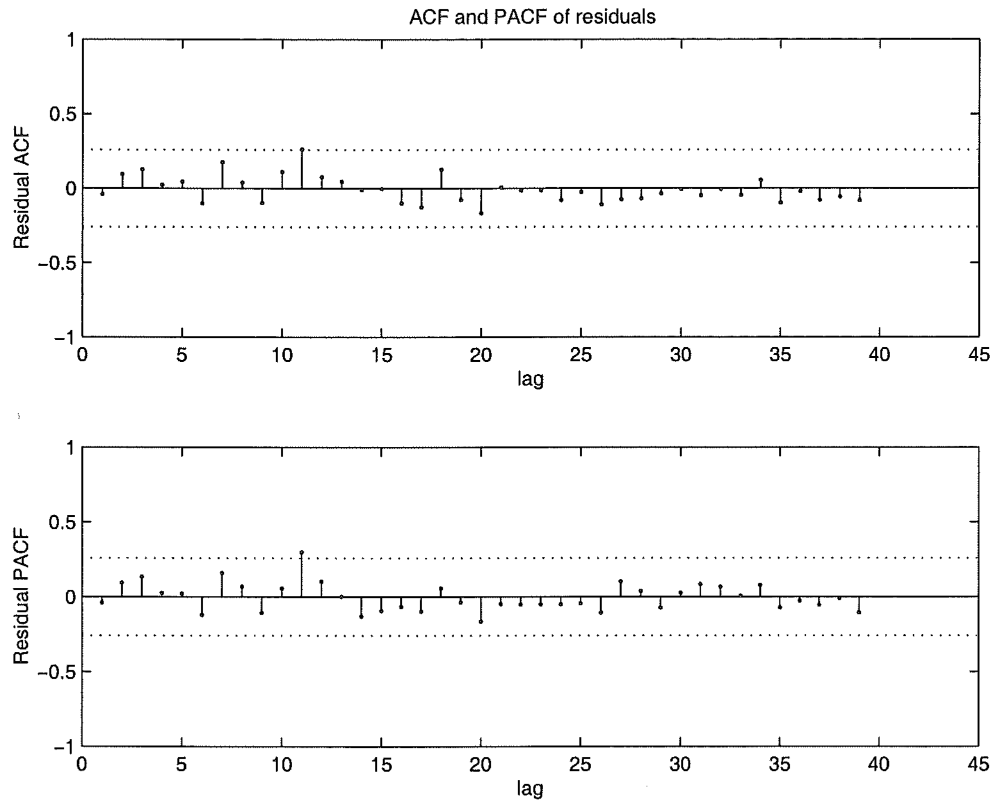

Figure 6.40 ACF and PACF of the residuals produced by the ARIMA(1,1,0) model for the Total electricity consumption

6.6 HARVEY LOGISTIC AND HARVEY MODELS

The Harvey Logistic and Harvey models are applied to the electricity consumption data of New Zealand [Mohamed and Bodger_2, 2004][2]. MATLAB programs are developed that performs the Harvey Logistic and Harvey modelling and forecasting as described in Section 4.5. The developed programs allow the application of Harvey models to any set of data with any number of data points to be used in forecasting.

---

[2] This work on electricity forecasting in New Zealand using the Harvey Logistic and the Harvey models have been accepted for publication in the international journal *Technological Forecasting and Social Change* [Mohamed and Bodger_2, 2004].

6.6.1 Harvey Logistic Model

The Harvey Logistic model is applied separately to each of the Domestic and the Non-Domestic sectors and the Total electricity consumption data. Regressing $\ln\left(\frac{y_t}{Y_{t-1}^2}\right)$ as in Equation 4.44 over the time period 1943-1999 gives the following models.

Domestic:	$\ln y_t = 2\ln Y_{t-1} + 150.86 - 0.083t$	(6.25)
Non-Domestic:	$\ln y_t = 2\ln Y_{t-1} + 145.79 - 0.080t$	(6.26)
Total:	$\ln y_t = 2\ln Y_{t-1} + 145.60 - 0.081t$	(6.27)

A plot of $\ln\left(\frac{y_t}{Y_{t-1}^2}\right)$ along with the fitted regression line for the Domestic sector is shown in Figure 6.41.

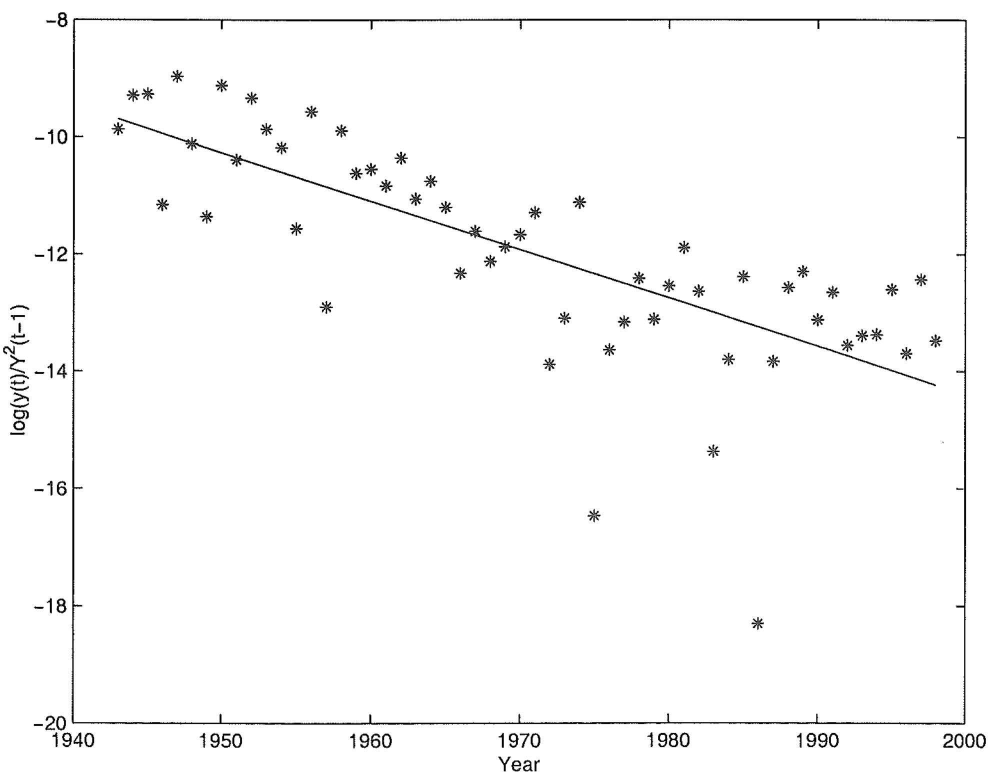

Figure 6.41 Plot of the regression line for the Domestic sector

The residuals of the regression fit are very well behaved with a Durbin-Watson (DW) statistic of 2.0 indicating that there is no correlation in the errors. The residuals of the regression fits are also reasonably well behaved in the Non-Domestic sector and the Total consumption, with Durbin–Watson statistics of 1.1 and 1.5, although there is some indication of serial correlation in the case of Non-Domestic data.

Figure 6.42 shows the fitted Harvey Logistic models for the Domestic and the Non-Domestic sectors, and the Total electricity consumption. The Harvey Logistic models have produced very good fits of the electricity consumption data with mean absolute percentage errors (MAPE) values of 3.1 for the Domestic, 3.3 for the Non-Domestic and 2.6 for the Total consumption data. The DW values corresponding to these fits are 1.96, 1.56 and 1.71 for the Domestic, the Non-Domestic and the Total electricity consumption respectively. These DW values are very close to the desired value of 2 indicating that the residuals are white noise and the models can be accepted for forecasting electricity.

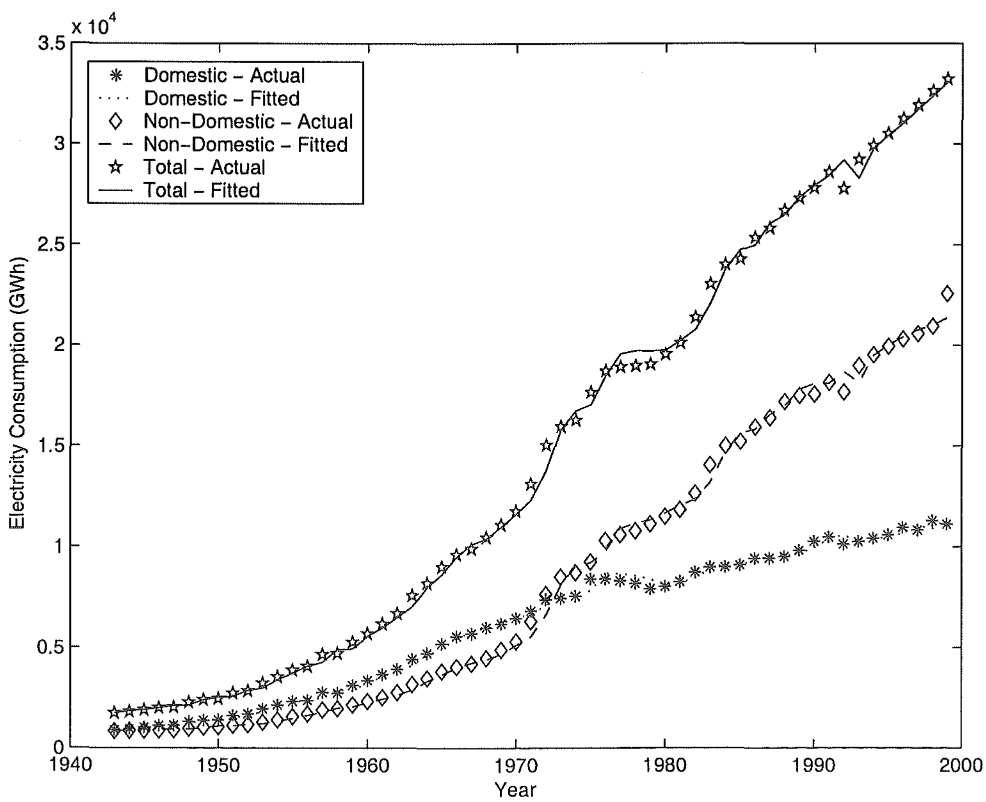

Figure 6.42 Fitted Harvey Logistic models for electricity consumption in New Zealand

6.6.2 Harvey Model

Application of the electricity consumption data to the Harvey model (Equation 4.49) resulted in the following models.

Domestic: $$\ln y_t = 0.60 \ln Y_{t-1} + 35.44 - 0.018t \quad (6.28)$$

Non-Domestic: $$\ln y_t = 1.29 \ln Y_{t-1} + 57.46 - 0.032t \quad (6.29)$$

Total: $$\ln y_t = 1.08 \ln Y_{t-1} + 50.27 - 0.028t \quad (6.30)$$

where, t is the time in years from 1944 to 1999.

The fitted Harvey models for the historic data of the Domestic and the Non-Domestic sectors and Total consumption are shown in Figure 6.43.

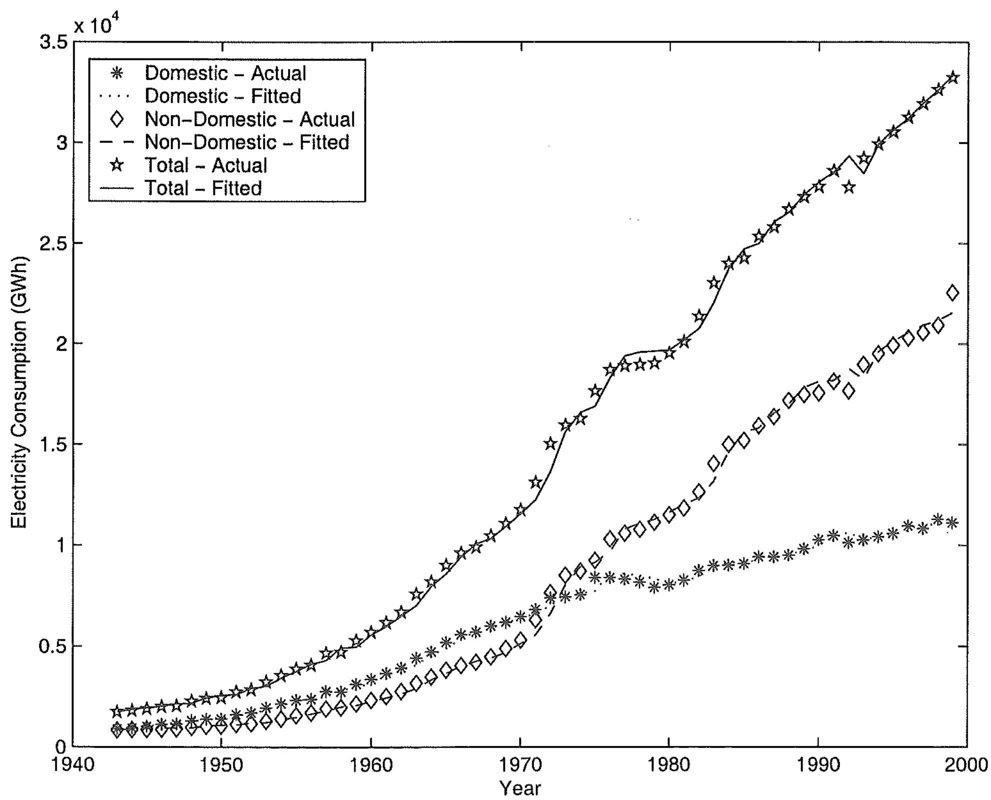

Figure 6.43 Fitted Harvey models for New Zealand electricity consumption

These Harvey models have produced very good fits with MAPE values of 3.1 for the Domestic, 3.3 for the Non-Domestic and 2.7 for the Total consumption. These values are very close to the Harvey Logistic model fits. As seen from Equation 6.28 to 6.30, the coefficients of Y_{t-1} are significantly different from the 2 of those in the Harvey Logistic models. These values indicate that the Harvey models are different from the Harvey Logistic models proposed. In addition the Harvey models gave DW values of 1.89, 1.55 and 1.67 for the Domestic, the Non-Domestic and the Total electricity consumption respectively. All these values are close to 2 indicating that the residuals produced by the fitted models represent white noise. Therefore, the Harvey models have been accepted for forecasting electricity consumption in New Zealand.

6.7 VARIABLE ASYMPTOTE LOGISTIC (VAL) MODEL

The Variable Asymptote Logistic (VAL) technique described in Section 4.6 is applied to the electricity consumption data of New Zealand [Mohamed and Bodger_3, 2004][3]. This section explains in detail the application of the VAL model in forecasting electricity consumption in New Zealand.

6.7.1 Initial Estimation of Saturation Levels

Initial values of the saturation level are obtained by the Fibonacci search technique. The Fibonacci search technique is applied to the Domestic, the Non-Domestic and the Total electricity consumption data series 1943-1980, 1943-1981, ..., 1943-1999 of New Zealand and the saturation level F is estimated for each case. The corresponding saturation levels are shown in Figure 6.44. The Domestic saturation level is relatively constant with a slight increase over the data period. The Non-Domestic saturation level was consistently decreasing until the early 1990's. The decrease of the saturation level in the initial years suggests possible immaturity in the Non-Domestic data. However,

[3] This work on electricity forecasting in New Zealand using the VAL model has been accepted for publication in the *International Journal of Computer Applications in Technology* in a special issue on 'Intelligent Systems for Intelligent Energy in the New Millennium' [Mohamed and Bodger_3, 2004].

the near constant value beyond 1992 suggests possible maturity in the latter years. The Total consumption saturation level is relatively constant with an increase in value after 1984. The restrictions on electricity brought by the draught of 1992 are reflected in the variation of the saturation level of the Non-Domestic consumption for that year, with an overall low saturation beyond 1994. This is not very significant in the Domestic or the Total consumption. In all cases, deregulation of electricity in New Zealand in 1987 appears to have had little or no influence in the patterns.

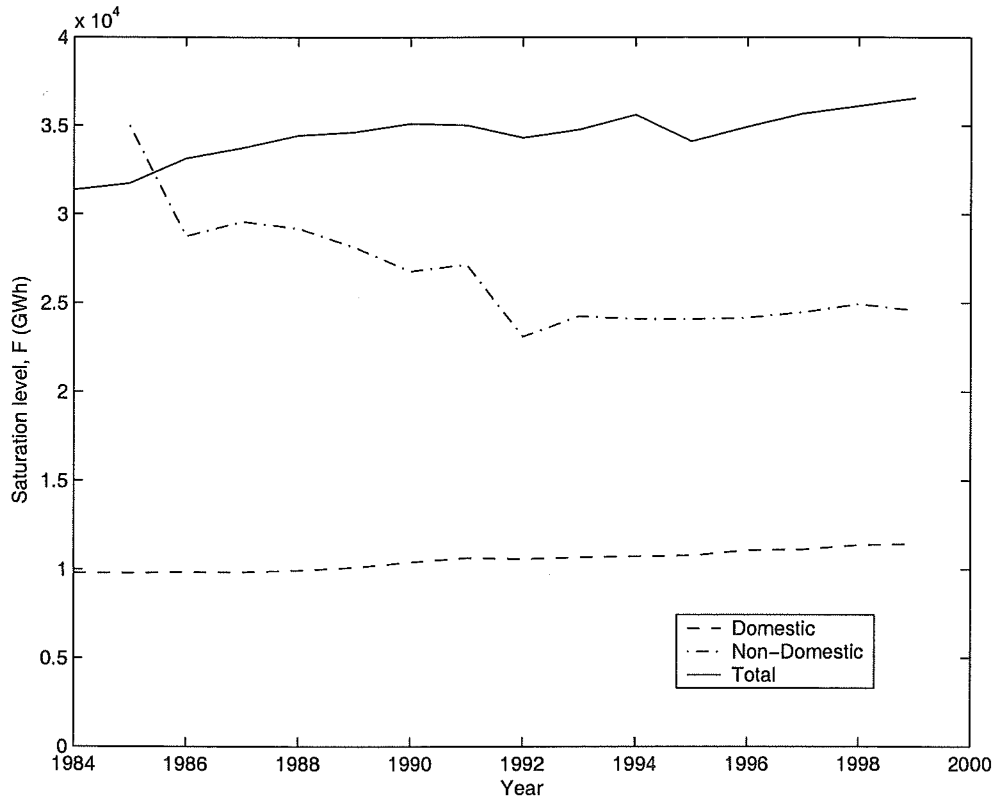

Figure 6.44 Saturation levels using Fibonacci search technique

6.7.2 Correlation and Re-estimation of F

In order to use population, price of electricity and GDP in estimating the saturation levels, it is expected that the chosen variables effectively explain the respective saturation levels. Table 6.21 shows the correlation between the saturation levels and the explaining variables considered.

Table 6.21 Correlation between the saturation levels and the explaining variables

Saturation	Explaining variables		
	Population	Price	GDP
Domestic	0.95	0.81	0.88
Non-Domestic	-0.49	-0.61	-0.51
Total	0.68	0.67	0.61

The correlation is high in the Domestic sector. The correlation in Total consumption is also acceptable while those for the Non-Domestic sector is negative and much lower in magnitude overall. The negative correlation in the Non-Domestic sector is the result of an overall decrease in saturation levels in the Non-Domestic consumption as opposed to the Domestic and Total consumptions. This indicates immaturity in the Non-Domestic sector and that the growth in the Non-Domestic sector has not gone beyond the early stages of development for the Fibonacci search technique to be applied effectively. In addition, the low correlation in the Non-Domestic sector has excluded the possibility of applying the VAL model the Non-Domestic sector.

Durbin-Watson statistic, coefficient of determination and *F*-test are used in evaluating the applicability of the estimated saturation levels using the explaining variables [Makridakis *et al.*, 1998]. Initially, the saturation levels are estimated using combinations of all these three variables. The process of re-estimation is continued with not only the various combinations of variables, but also with the various saturation level data sets. It was found that all the combinations of the variables are generally acceptable for the saturation data sets of the range from 1980-1999 to 1985-1999. The best results are found for the data set from 1984-1999. Table 6.22 summarises the statistical test results and the various combinations of explaining variables used for the saturation data set 1984-1999.

The combination of population and GDP in Model 3 for the Domestic sector is the best. However, the corresponding results for the Total consumption are not satisfactory. The DW, r^2 and *F*-statistics values are much lower than all the other combinations of explaining variables chosen. Model 4 performs the worst for both the Domestic and

Total consumption. Models 1 and 2 are the most comparable in terms of the statistical tests. In Model 1, the addition of a third explaining variable has not improved the DW and r^2 statistical results significantly while the F-statistics have decreased. Overall it is Model 2 that performs most consistently. In all the models, the DW values of the Domestic sector are much closer to 1 (rather than being closer to 2) indicating some serial correlation of the residuals.

Table 6.22 Statistical test results of the various models for the data set from 1984-1999

Variables in the Model	Domestic			Total			99%
	DW	r^2	F	DW	r^2	F	critical F
1. Population, Price and GDP	1.0	0.97	117.1	1.7	0.85	21.8	5.0
2. Population and Price	0.9	0.96	147.4	1.7	0.84	35.0	5.6
3. Population and GDP	1.0	0.97	187.5	0.7	0.60	9.6	5.6
4. Price and GDP	0.8	0.88	45.7	1.6	0.84	34.6	5.6

The corresponding estimates of the saturation values for each of these models are

Model 1:

$$\begin{aligned} F_{D1}(X) &= -6.08\times10^{2} + 3.6\times10^{-3} X_1 + 18.5 X_2 - 2.33\times10^{2} X_3 \\ F_{T1}(X) &= 2.95\times10^{4} - 1.16\times10^{-3} X_1 + 1.05\times10^{3} X_2 + 2.54\times10^{-2} X_3 \end{aligned} \tag{6.31}$$

Model 2:

$$\begin{aligned} F_{D2}(X) &= 9.46\times10^{2} + 2.6\times10^{-3} X_1 + 42.1 X_2 \\ F_{T2}(X) &= 2.79\times10^{4} - 5.28\times10^{-4} X_1 + 1.03\times10^{3} X_2 \end{aligned} \tag{6.32}$$

Model 3:

$$\begin{aligned} F_{D3}(X) &= -931 + 3.8\times10^{-3} X_1 - 2.49\times10^{-2} X_3 \\ F_{T3}(X) &= 1.11\times10^{4} + 8.0\times10^{-3} X_1 - 6.42\times10^{-2} X_3 \end{aligned} \tag{6.33}$$

Model 4:

$$F_{D4}(X) = 5.74\times10^{3} + 182X_2 + 4.16\times10^{-2}X_3$$
$$F_{T4}(X) = 2.67\times10^{4} + 977X_2 - 3.8\times10^{-3}X_3 \qquad (6.34)$$

Where, X_1 is population, X_2 is price of electricity, X_3 is GDP, and $F(X)$ denotes the saturation function with respect to the subscript D for Domestic sector and T for the Total consumption.

6.7.3 VAL Method and Forecasting

In the Logistic model, the asymptote F calculated for a particular data set is a constant for the forecast to be made. If a forecast is to be made from the year 2000 onwards, the Fibonacci search technique is used to obtain a constant F, which is then used in Equation 4.4, as the time t is increased to obtain the forecasts. In the VAL model, the asymptote F for each of the forecasted years is different from one another. ARIMA methods are used in forecasting population, price of electricity, and GDP. The forecasts of these explaining variables are used to calculate the saturation values of electricity for the future years using Equation 6.31 to Equation 6.34.

6.7.4 Model Selection using Forecasting Accuracy

Forecasting accuracies of the four models are measured over the period from 1991 to 1999. In making the forecast for 1999, all the data up to 1998 is used. The forecasting accuracy is measured by calculating the mean absolute percentage error (MAPE) of the 1 year ahead forecast. Similarly, the MAPE values from two years ahead through to nine years ahead forecasts for the Domestic Sector are calculated and are shown in Figure 6.45. The best forecast is for Model 2 giving the lowest MAPE values from 1 year through to 7 years ahead forecasts. Initially, Models 1 and 3 behaved very similarly but Model 1 performed better for the longer forecasting periods. Model 4 performed better than Models 1 and 3 initially, but gave much higher errors from 6 years ahead onwards. The MAPE values of one year through to nine years ahead forecasts of the Total electricity consumption are shown in Figure 6.46.

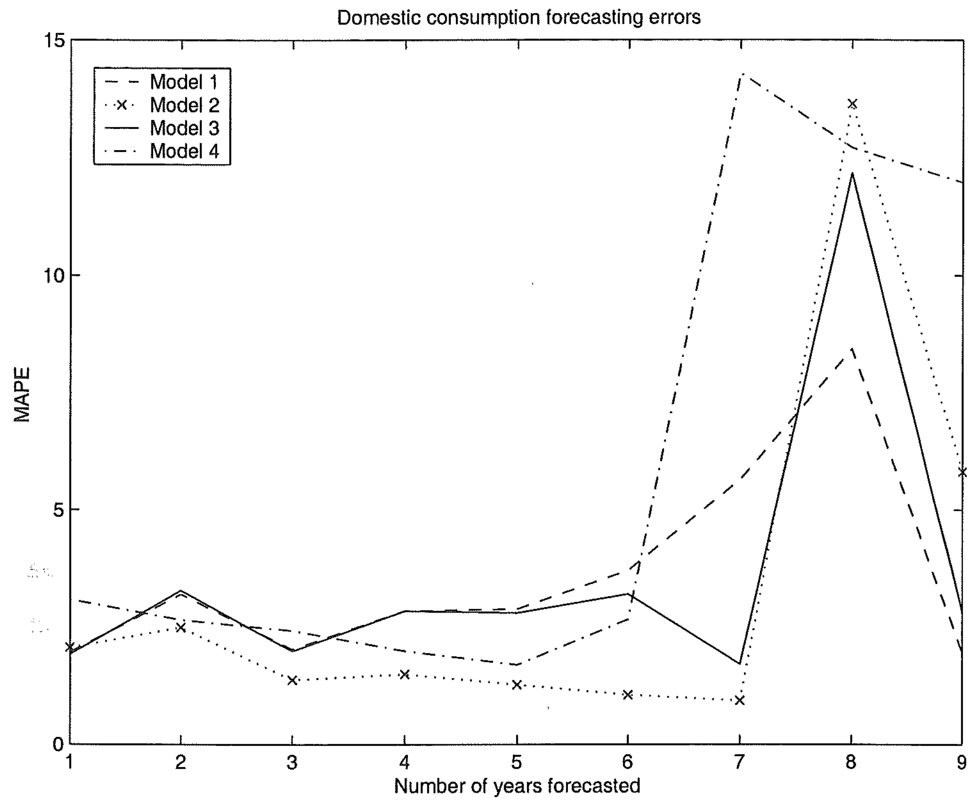

Figure 6.45 Forecasting accuracies of the four models for Domestic sector

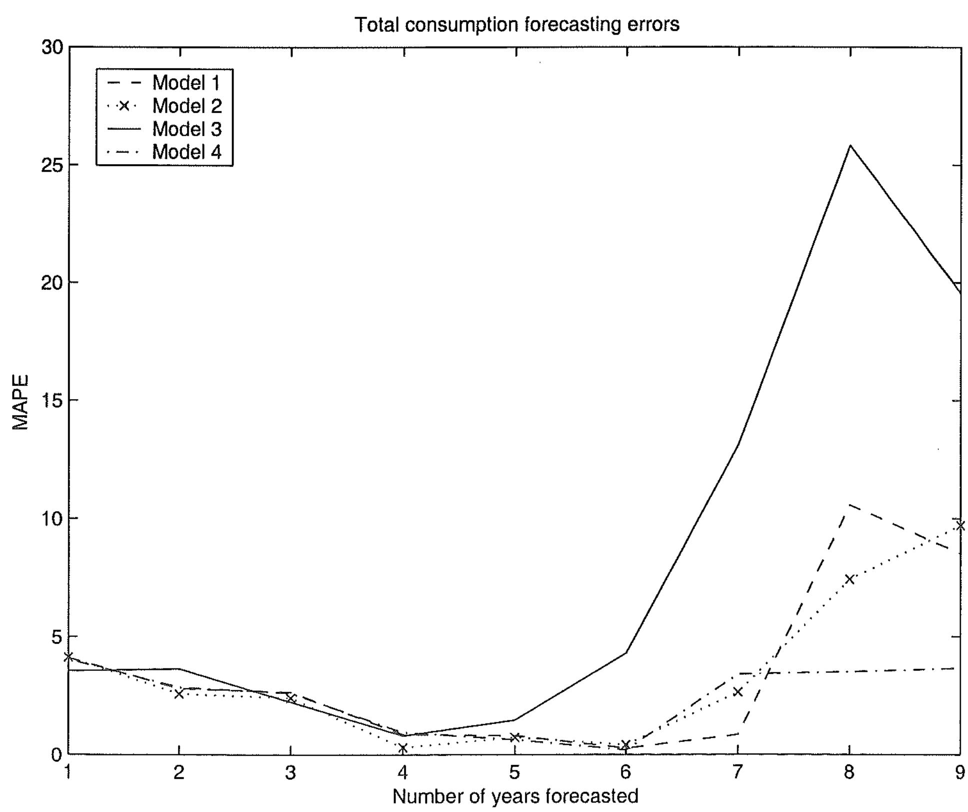

Figure 6.46 Forecasting accuracies of the four models for the Total electricity consumption

The forecasting errors in the Total consumption are closer together especially in the short range forecasts. However, Model 2 again gave the lowest MAPE values from 1 year through to 6 years ahead errors. It can also be seen that Model 1 gave the highest MAPE values in general, indicating the worst forecasts.

Beyond year 7, the forecasts of all the models are generally weak giving rise to high MAPE values, especially at year 8. There are two possible reasons for this. Firstly, in the VAL method, the asymptotes are estimated for the years from 1984. Thus, in the 8 years ahead forecast the saturation levels are initially calculated from 1984 to 1991. This means that as the forecasted period increases, the number of saturation values calculated decreases. The decrease in the number of data points generally increases the error in the estimate of the coefficients in the regression analysis [Farnum and Stanton, 1989]. This will lead to an increase in forecasting errors. Secondly, for both the Domestic and the Total consumption data, the decrease in consumption in the year 1992 due to the electricity restrictions brought by the drought in that year resulted in an overall increase in the forecasting error.

In terms of forecasting accuracy, Model 2 is the best model for forecasting electricity consumption. This model uses only population and price of electricity as the explaining variables.

6.7.5 Proposed VAL Model for New Zealand

Analyses in the two previous sections show that the best VAL model uses population and price of electricity as the explaining variables. Therefore this model is chosen as the VAL model for electricity consumption in New Zealand. The estimated Domestic and Total consumption saturation levels using the VAL model are shown in Figure 6.47. There is a good correlation between the actual saturation values obtained by the Fibonacci search technique and those estimated by the VAL model.

The proposed VAL model for the Domestic sector is

$$f_D = \frac{F_{D2}(X)}{1+\exp(-200+0.104t)}$$

$$= \frac{9.46\times10^2 + 2.6\times10^{-3}X_1 + 42.1X_2}{1+\exp(-200+0.104t)} \tag{6.35}$$

And the proposed VAL model for Total consumption is

$$f_T = \frac{F_{T2}(X)}{1+\exp(-185+0.094t)}$$

$$= \frac{2.79\times10^4 - 5.28\times10^{-4}X_1 + 1.03\times10^3 X_2}{1+\exp(-185+0.094t)} \tag{6.36}$$

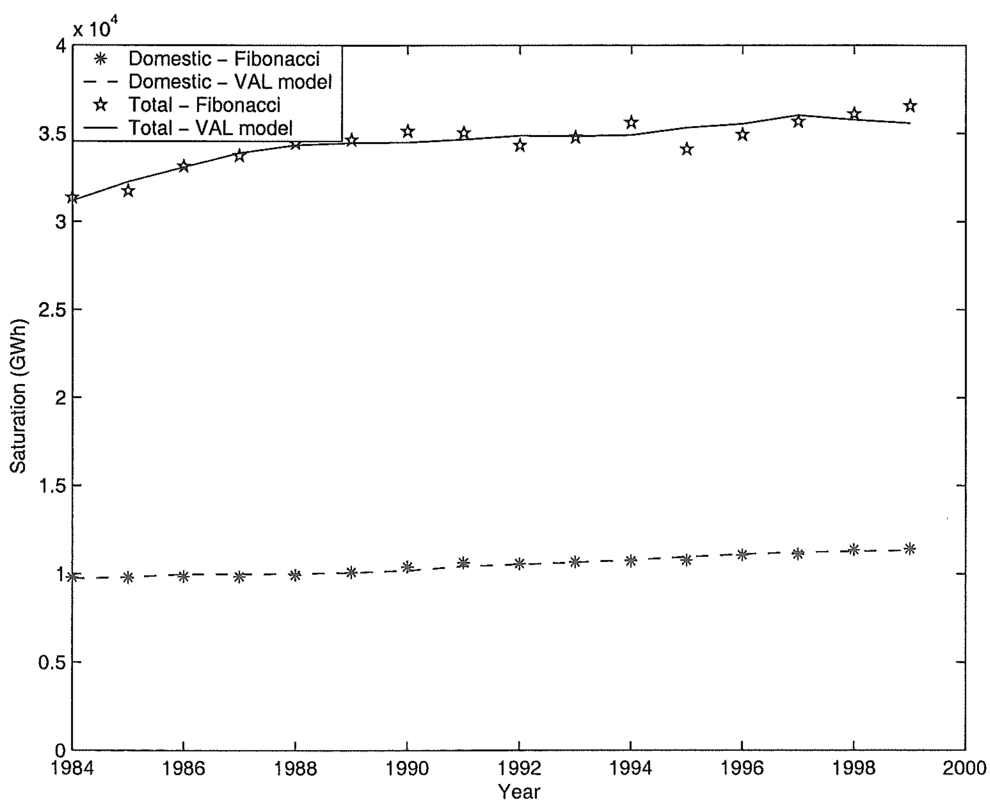

Figure 6.47 Saturation estimation by the VAL models

6.7.6 Comparison with the Logistic Model

In addition to overcoming the constraints of the Logistic model, the initiative to the development of the VAL model is to increase the forecasting accuracy. This should be reflected in a reduction in the forecasting errors. If the VAL model does not reduce the forecasting error, then the choice of this model over the Logistic model could not be supported.

The quality of forecasting of the VAL models can be visually obtained by observing how well the models have forecasted actual data. Figure 6.48 shows the forecasts of the VAL model and the Logistic model along with the actual consumption from 1995 to 1999. In making these forecasts, it was assumed that no data beyond 1994 is known. The forecasts by the VAL model are much better than the forecasts by the Logistic model for the 5 year ahead forecasts.

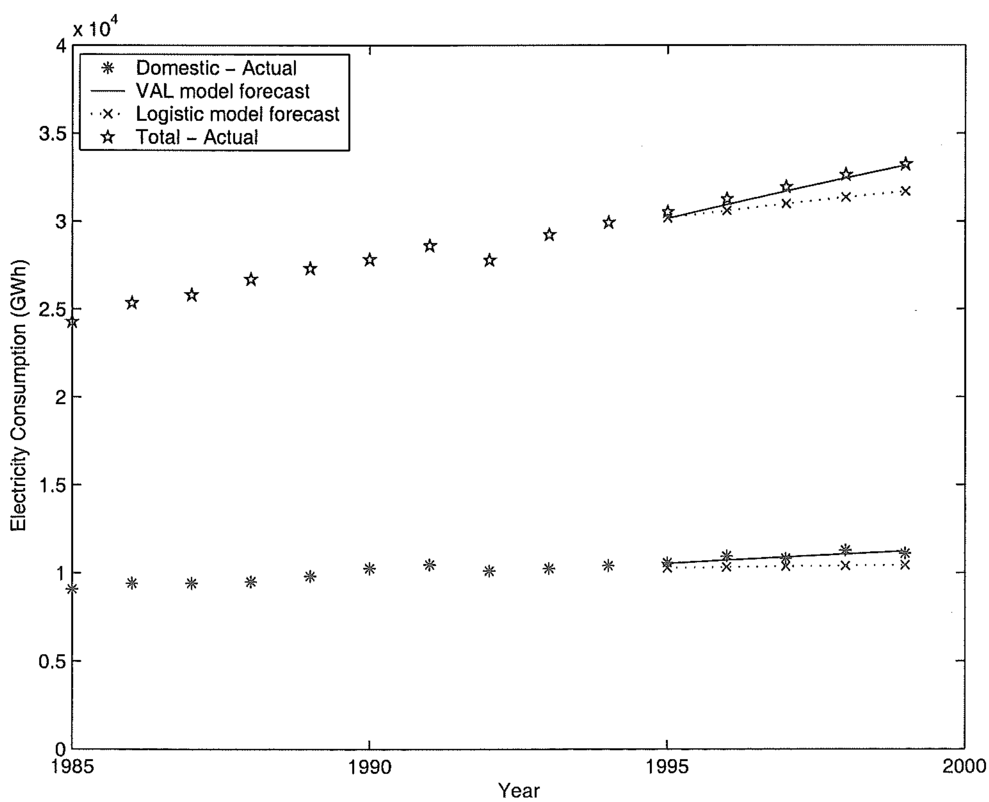

Figure 6.48 Comparison of forecasts by VAL model and Logistic model

The MAPE values for the Domestic consumption are 1.3 for the VAL model while there is a much higher value of 5.3 for the Logistic model. Similarly, the MAPE value for the Total electricity consumption is 0.7 for the VAL model while that for the Logistic model is 2.9. These values clearly suggest that the VAL model has performed much better. The forecasting errors, using MAPE, are calculated not only for the 5 year ahead forecasts but from 1 year ahead to 9 years ahead forecasts (1991 to 1999) for the VAL and Logistic models. The resulting MAPE values are shown in Figure 6.49.

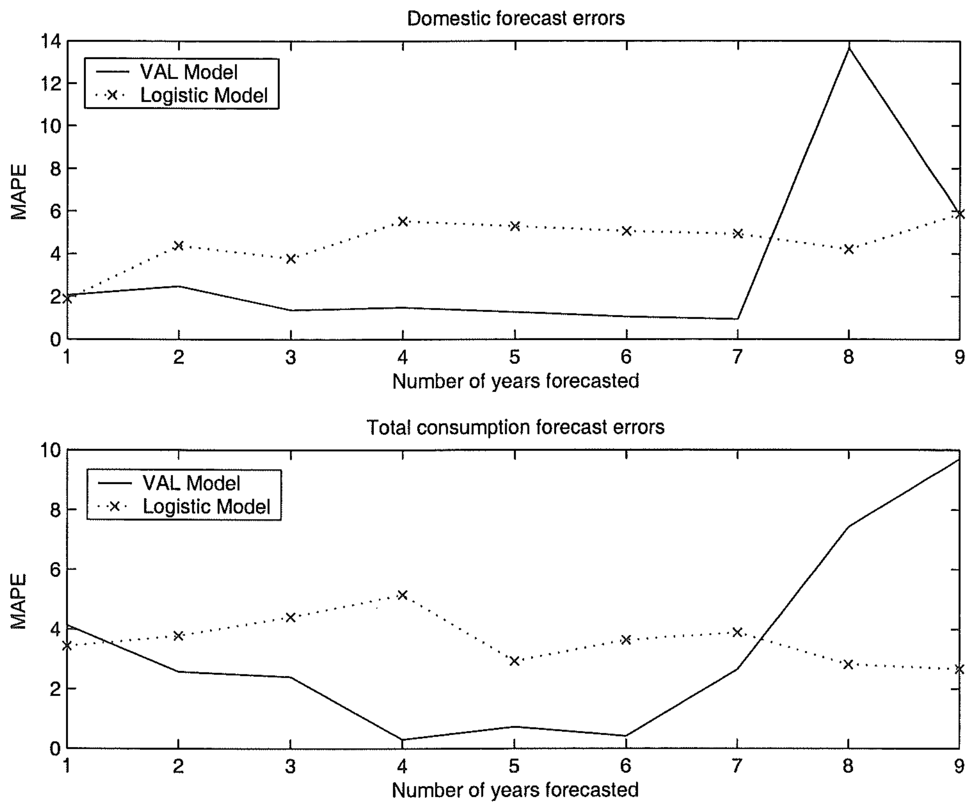

Figure 6.49 Forecasting accuracies of the VAL and Logistic models

The MAPE values are much lower for the VAL model from 1 year ahead through to 7 years ahead forecasts for both the Domestic and the Total electricity consumptions. At year 8, the VAL model has higher MAPE values than the Logistic model, again reflecting the drought year of 1992 which could not have been predicted by the change in population and price of electricity in the VAL model as compared to the Logistic model. Overall, the VAL model has given rise to more accurate forecasts than the Logistic model. Therefore, the VAL models are accepted for forecasting electricity consumption in New Zealand.

6.8 COMPARISON OF MODELS

The developed models for electricity forecasting in New Zealand are compared for goodness of fit to the historical data, and forecasting accuracy in the short, medium and long term. The forecasts of these models are also compared with the available national forecasts in New Zealand [Sinclair Knight Merz, 2000] [MED, 2000].

6.8.1 Model Fit and Forecasting Accuracy

Forecasting accuracy is measured from one year ahead through to nine years ahead for all models. For example, to calculate the MAPE of the 9 years ahead forecasts, the actual electricity consumption data from 1991-1999 (n = 9) is held out while developing these models. The forecasts obtained by the models and the actual consumption data held out are then used to calculate the MAPE value. The MAPE plots of the six models from one year ahead through to nine years ahead are shown in Figure 6.50.

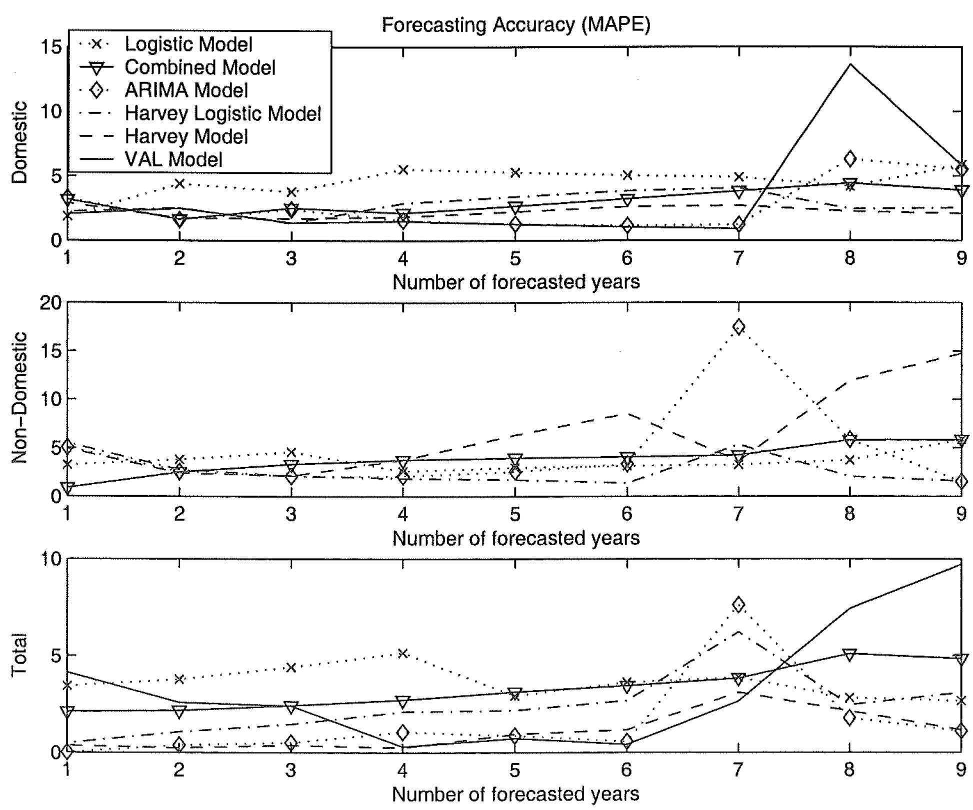

Figure 6.50 Forecasting accuracies of the six developed models for New Zealand

The models are ranked according to their level of model fit, short term (1 to 3 years), medium term (4 to 6 years) and long term (7 to 9 years) forecasting accuracy. Models are ranked from 1 (best) to 6 (worst) for the Domestic and the Total consumption, while 1 (best) to 5 (worst) for the Non-Domestic consumption as the VAL model was not applicable (n/a) for this sector. The average of the MAPE values over the short, medium and long term is calculated. Models are ranked from the lowest MAPE (best model) to the highest MAPE (worst model). The overall rankings for the Domestic, the Non-Domestic and the Total consumption are calculated by taking the average of the MAPE values over the nine year period compared. Table 6.23 summarises the results.

Table 6.23 Rankings of the models for New Zealand (1 = best, 6 = worst)

Model	Domestic					Non-Domestic					Total				
		Accuracy					Accuracy					Accuracy			
	fit	Short	medium	long	**Overall**	fit	Short	medium	long	**Overall**	fit	Short	medium	long	**Overall**
Logistic	6	6	6	5	**6**	4	5	3	2	**2**	4	6	6	2	**6**
Combined	1	5	4	3	**4**	5	1	4	3	**3**	5	4	5	5	**4**
ARIMA	4	4	2	4	**2**	3	3	2	4	**4**	3	1	3	3	**2**
Harvey Logistic	2	2	5	2	**3**	2	4	1	1	**1**	2	3	4	4	**3**
Harvey	3	3	3	1	**1**	1	2	5	5	**5**	1	2	2	1	**1**
VAL	5	1	1	6	**5**			n/a			6	5	1	6	**5**

6.8.1.1 Domestic Sector

The best model fit is given by the Combined model. The short term forecasts given by all the models except the Logistic are very comparable. The VAL model gave the best short and medium term forecasts, while it is ranked the worst in forecasting the long term. The best model for forecasting the long term is the Harvey model. The worst forecasts for the short and the medium term are given by the Logistic model. Overall, the Harvey model gave the best accuracy in the Domestic sector followed by the

ARIMA model. There is a sudden jump in MAPE for the VAL model at year 8. Possible reasons for this variation have already been explained in Section 6.7.4.

6.8.1.2 Non-Domestic Sector

The best model fit is given by the Harvey model. The forecasts given by the ARIMA, Harvey Logistic and Harvey models are very close for the short term. The Combined model gave the best short term forecasts while the Harvey Logistic model gave the best medium and long term forecasts. The worst forecasts are given by the Logistic model for short term and by the Harvey model for the medium and long term forecasts. Overall, the Harvey Logistic model gave the most accurate forecasts in the Non-Domestic sector followed by the Logistic model.

There is a large increase in error at year 7 by the ARIMA model. This corresponds to the forecasts made from the drought year of 1992. The consumption is significantly lower for this year due to electricity restrictions. The ARIMA forecasts are very dependent on the latest data of the actual consumption. Thus, the overall forecast made for the 7 years ahead is much lower. This resulted in a significant increase in error as shown in Figure 6.50.

6.8.1.3 Total Consumption

The best fit is again given by the Harvey model. The Harvey and ARIMA models gave very low MAPE values from year 1 to year 6. The ARIMA model was ranked the best for short term forecasting. The sudden decrease in MAPE by the VAL model at year 4 to 6 resulted in that model being the best to forecast the medium term. The Harvey model gave the best long term forecast. The Logistic and VAL models gave the worst Total electricity consumption forecasts. Overall, the Harvey model gave the best forecasts for the Total electricity consumption followed closely by the second best ARIMA model.

It was reported that a 10% error in forecasting is generally acceptable for long term load forecasting of Japanese power companies when an artificial neural network (ANN) model was used [Kermanshashi and Iwamiya, 2002]. The ANN model was able to forecast loads with a 3% forecasting error. The developed Harvey model for the electricity consumption in New Zealand gave the most accurate forecasts among the six developed models. This model gave an average error of just over 1% (1.08%) while the second best ARIMA model gave a 1.5% forecasting error in the Total electricity consumption. Even the Logistic model which is ranked the worst gave an error of 3.6% for the Total consumption.

6.8.2 Comparison of Forecasts

In New Zealand, electricity consumption forecasts are published by the Centre for Advanced Engineering (CAE) [Sinclair Knight Merz, 2000] and the Ministry of Economic Development (MED) [MED, 2000]. The CAE forecasts are modelled using an annual load growth of 1.8%. Their study has used 1.8% as the baseline estimate, with 1.3% and 2.3% growth used for sensitivity analysis. This research uses the 1.8% baseline estimate for comparison purposes.

The MED forecasts are made by the Ministry of Economic Development, New Zealand, using its Supply and Demand Energy Model (SADEM) [MED, 2000]. SADEM is a descriptive market equilibrium model focusing on the entire energy sector. The model determines equilibrium in the energy market by projecting demands for a given set of prices and comparing this with the modelled cost of supplying this level of demand [MED, 2000]. The SADEM model is a deterministic model as it produces a single projection for a given set of assumptions. The demand model provides annual projections of energy demand and are generally dynamic models providing a short-run and long-run response to changes in prices, incomes and other drivers [MED, 2000]. The supply side electricity is run every five years beginning in 2000, and prices are interpolated between these dates, resulting in an increase in electricity capacity once every five years to meet the demand. The MED forecasts are given for every five years from 2000. As an interpolation technique is used for updates of the prices, the forecasts are also interpolated between these dates.

The forecasts obtained by all the models from the year 2000 to 2015 for the Domestic, the Non-Domestic and the Total electricity consumption are shown in Figure 6.51 to 6.53 respectively. For the Domestic sector, the highest forecasts are given by the MED model followed by the CAE model. The forecasts by the Combined model and the ARIMA model are very similar especially for the long term forecasts. The Harvey model, which gave the most accurate overall performance of all the developed models, gave forecasts that are approximately an average of all the other models.

For the Non-Domestic sector, the ARIMA model predicted the highest consumption values followed by the Harvey model. The forecasts by the most accurate Harvey Logistic model gave forecasts that are very similar to the CAE and MED forecasts especially in the long term. The forecasts of the Combined model are more similar to but less than the Harvey model forecasts.

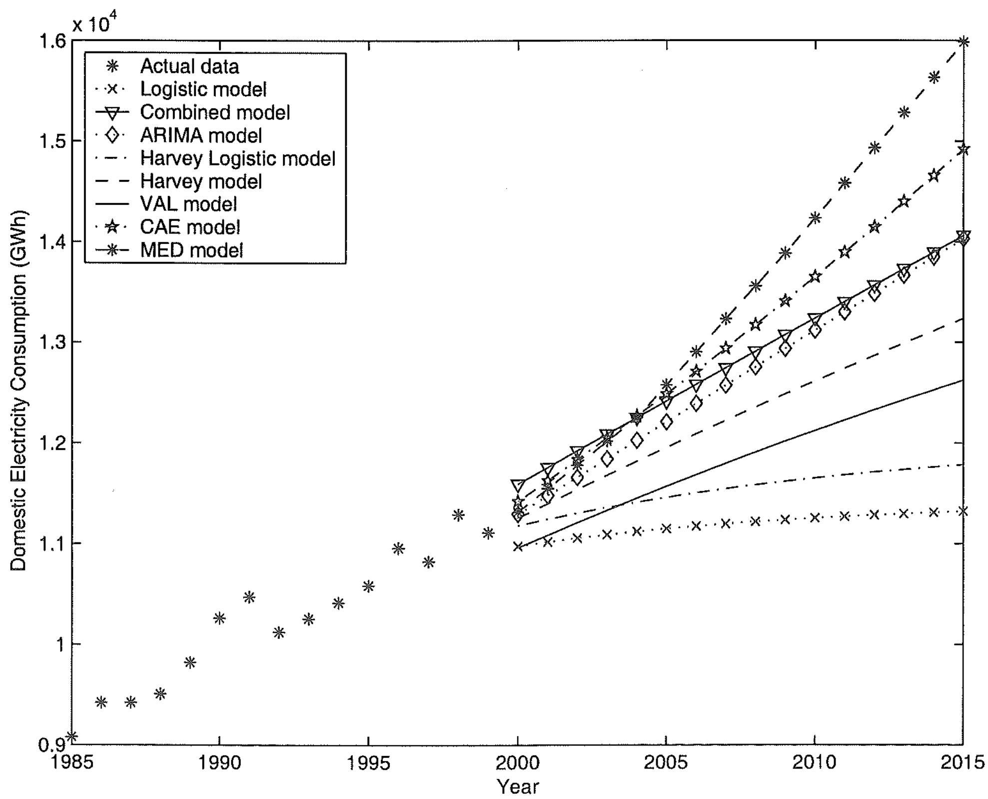

Figure 6.51 Comparison of forecasts for the Domestic sector of New Zealand

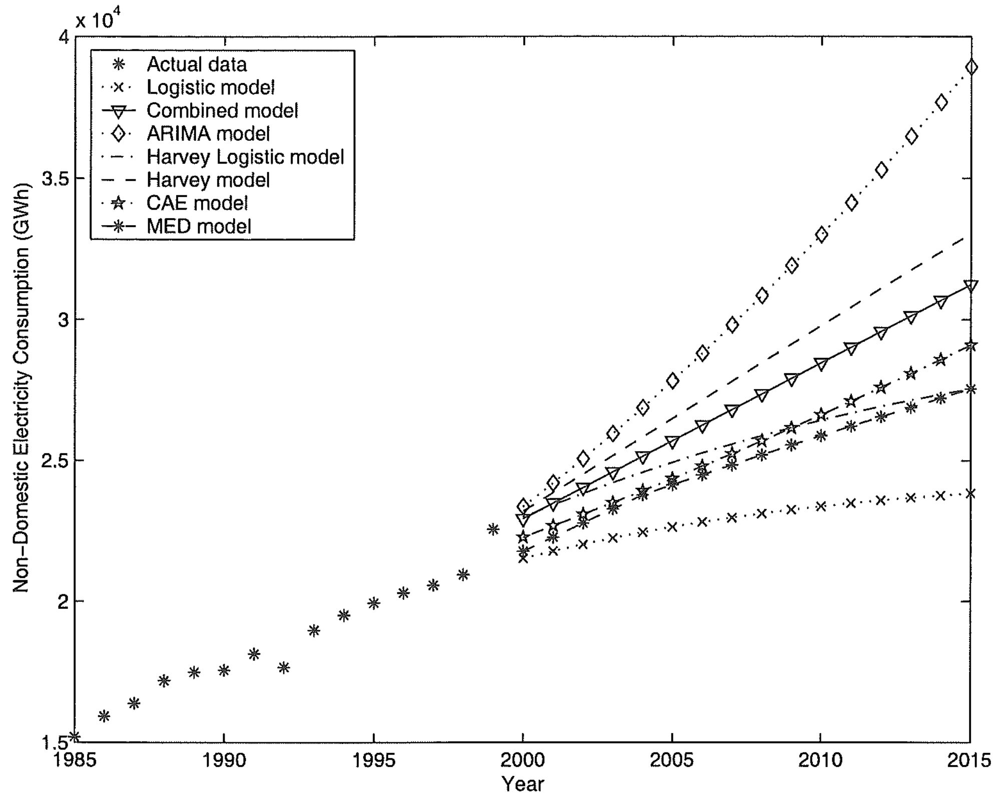

Figure 6.52 Comparison of forecasts for the Non-Domestic sector of New Zealand

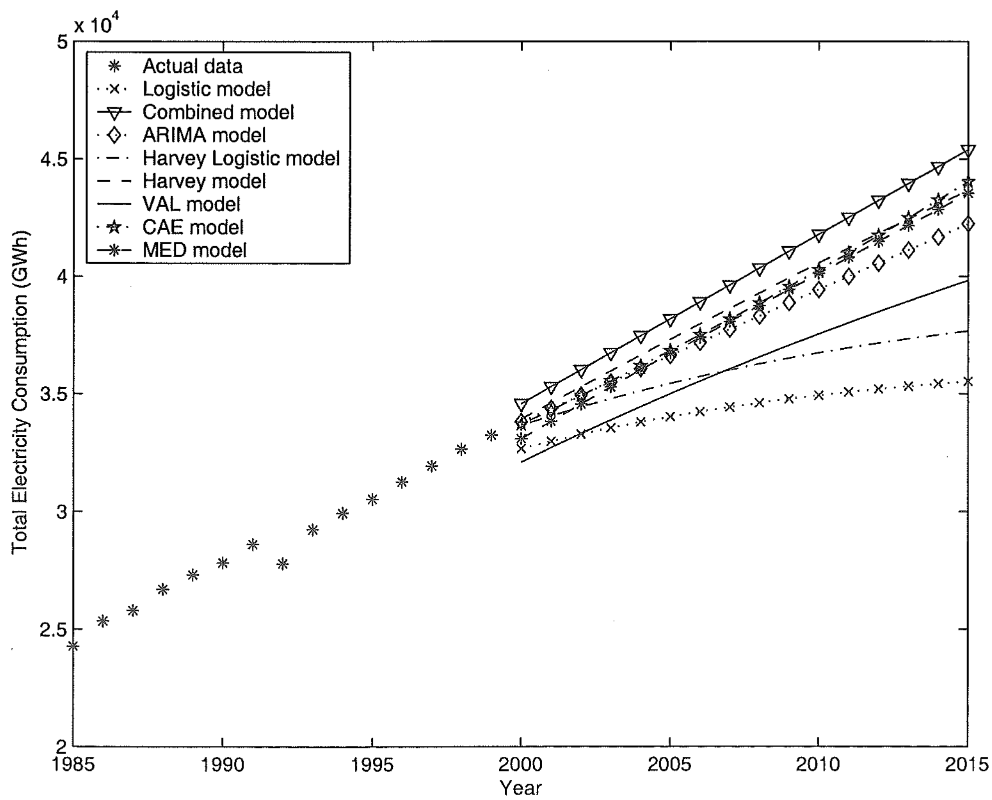

Figure 6.53 Comparison of Total electricity consumption forecasts for New Zealand

For the Total consumption, forecasts given by the most accurate Harvey model developed for New Zealand are very comparable with the CAE and the MED model forecasts. Forecasts by the ARIMA models are also very similar to these three models especially for the early years. Although the Combined model forecasts are also close to these forecasts, its forecasts are a little higher on average than these models. The VAL model initially started with lower predictions than the Logistic model, but ultimately predicted higher consumption values than the Logistic and the Harvey Logistic models. In all cases, the Logistic models have predicted the lowest consumption values followed by the Harvey Logistic models.

6.9 SUMMARY

This chapter has developed and compared six forecasting models for electricity consumption in New Zealand where only limited national forecasts are published. Detailed analyses in the developments of the models have been described. The models were compared for goodness of fit to the historical data and forecasting accuracy in the short, medium and long term for each of the Domestic and the Non-Domestic sectors and the Total electricity consumption. The best model fits were given by the Combined model for the Domestic sector and the Harvey model for the Non-Domestic and the Total electricity consumption. Overall, the best forecasts were given by the Harvey models for both the Domestic and the Total electricity consumption and by the Harvey Logistic model for the Non-Domestic sector.

The developed electricity forecasting models for New Zealand gave low forecasting errors. The Harvey model gave the most accurate forecasts among the six developed models in this chapter. This model gave an average error of just over 1% while the second best ARIMA model gave a 1.5% forecasting error for the Total electricity consumption of New Zealand. When the forecasts given by the developed models are compared with the available national forecasts, it was found that the best ranked model for each data set gave forecasts that are comparable with the national forecasts.

Chapter 7

FORECASTING ELECTRICITY IN THE MALDIVES

7.1 INTRODUCTION

The Maldives is located in the Indian Ocean from $7^0 6'30''$ N to $0^0 41'48''$ S and $72^0 32'30''$ E to $73^0 45'54''$ E. The country consists of 1192 islands scattered across the ocean, of which 199 islands are inhabited [MPND, 2004]. The rest of the uninhabited islands include 87 developed as tourist resorts and a few islands developed for fisheries and agricultural activities [Ministry of Tourism, 2004]. The capital of the country, Male', is located near the middle of the country and contains the main government offices and is the centre of trade, commerce, business, health and education.

The latest census in the year 2000 indicated that the population of the country was 270,101 with 27.4% of the total population residing in the capital island Male' [MPND, 2004]. In terms of electricity consumption, Male' consumes about 70% of the total electricity in the whole country. Therefore, it has been targeted to forecast electricity consumption in Male'. It is believed that the electricity consumption in Male' will give an overall picture of the electricity consumption in the country as a whole. In the analysis to follow, the electricity consumption in Male' has sometimes been referred to as the Maldives.

In this chapter, the proposed electricity consumption forecasting models are applied to Male'. Details in the developments of the models to the Maldives are discussed. The developed models are also compared for forecasting accuracy in a similar way to New Zealand. Finally a comparison of forecasts given by the developed models is presented for electricity consumption in the Maldives.

7.2 ELECTRICITY CONSUMPTION IN MALE'

7.2.1 History of Electricity Development

Electricity was introduced to the Maldives on the 20 December 1949 using a 14 kW generator. In 1953, two 38 kW generators were installed [STELCO, 2004]. When these generators were installed, electricity was supplied to government offices, mosques and shops at the rate of one light bulb each. In 1958, two 75 kW generators were installed in the Old Power House and electricity was introduced for the first time to the public. In 1960, two 298 kVA generators were installed and 50 households were connected with electricity.

Since the introduction of electricity in 1949, a separate government office was formed to coordinate all the administrative and technical work. The name of the office has changed from the Electrical Department to Department of Electricity and later on to The Maldives Electricity Board (MEB) on 11 November 1982. In 1991, two 2.1 MW generators were installed and a new administrative block was constructed under the Power System Development Project in conjunction with the Asian Development Bank (ADB). The power distribution network of Male' was also upgraded under this project. To meet the rapid demand of electricity growth in Male', a Second Power System Development Project was initiated which installed another 2.1 MW generator in 1994, a 6 MW generator in 1996 and a 4.5 MW generator in 1998.

In June 1997, the president of the Maldives authorised legislation to form the State Electric Company (STELCO). STELCO is an entirely state-owned organisation responsible for the generation and supply of electricity to customers throughout the Maldives [STELCO, 2004]. In 2002 two 6.5 MW generators were installed under the Third Power System Development Project. Currently, the installed capacity for Male' is 29.56 MW with a firm capacity of 18.45 MW.

7.2.2 Electricity Consumption

The electricity consumption data is divided into the Domestic and Non-Domestic sectors and Total consumption, as for the analysis in New Zealand. The Domestic sector consists of residential customers while the Non-Domestic sector consists of manufacturing, commercial, government buildings and public places. The electricity consumption data for Male' is obtained from the Statistics Section of the Ministry of Planning and National Development [MPND, 2004] [MPND, 2003] and the State Electric Company [STELCO, 2004]. Appendix A lists the details of the data used. The annual electricity consumption data for Male' from 1980 to 2002 is shown in Figure 7.1. It can be seen that that there is an increasing trend in all the sectors. The Domestic and the Non-Domestic sectors follow a similar pattern of growth. The growth is approximately exponential (or early logistic) which is a constant percentage growth rate. Although there is a sudden increase in electricity consumption in the Domestic sector in the year 1993, no significant event or a change that has resulted in this increase could be found.

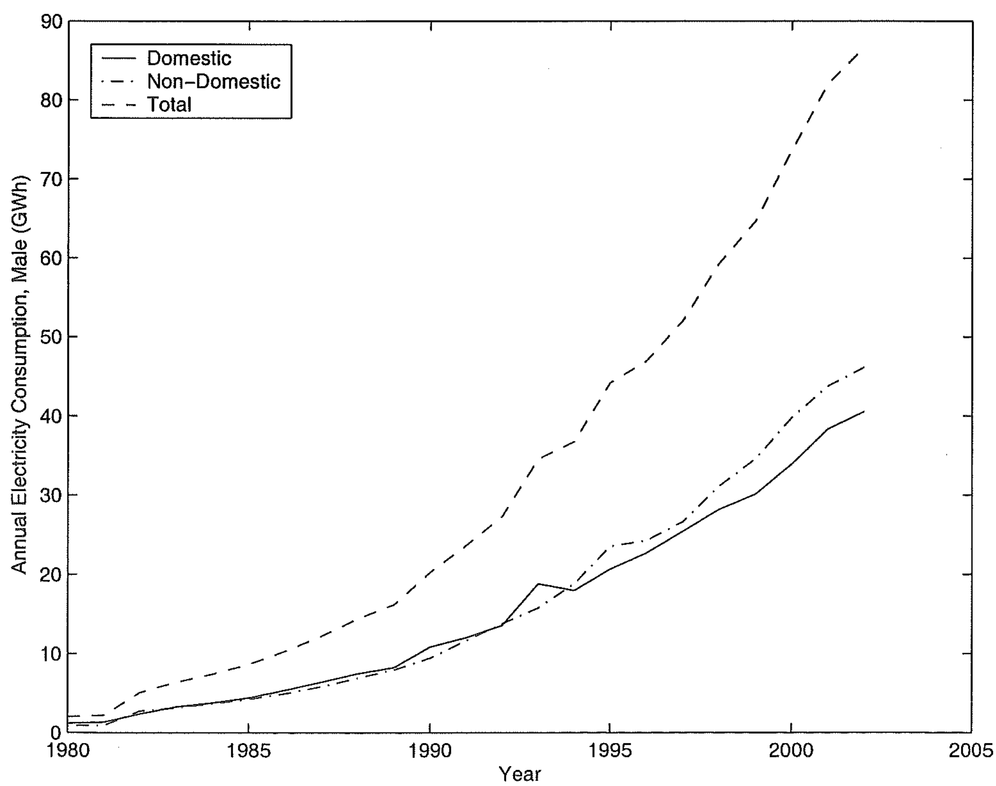

Figure 7.1 Annual electricity consumption in Male', Maldives

7.3 THE LOGISTIC MODEL

The asymptote *F* of the Logistic model is obtained by the Fibonacci search technique [Boas, 1963]. The resulting *F* values for the Male' data for the Domestic, Non-Domestic and Total consumptions are shown in Table 7.1.

Table 7.1 Asymptotic values for Male' by Fibonacci search technique

Sector	Data Year	F (GWh)
Domestic	1980-2002	53.0
Non-Domestic	1980-2002	69.6
Total	1980-2002	129.8

Unlike for New Zealand, the aggregate of the asymptotic values of the Domestic and the Non-Domestic sectors are not so close (within 6%) of that of the Total consumption. This indicates that both the Domestic and the Non-Domestic sectors have yet not gone beyond the early stages of development and may take sometime before heading towards maturity. The fitted Logistic models along with the actual data are shown in Figure 7.2. The corresponding mean absolute percentage errors (MAPE) are 6.6, 12.2 and 10.0 for the Domestic, the Non-Domestic and the Total electricity consumption respectively. The Logistic model has produced good fits of the historical data with similar MAPE values for all the sectors, indicating that the pattern of electricity consumption in Male' is more like a growth curve pattern. The poorest fit is in the Non-Domestic sector with a MAPE value of 12.2.

7.4 THE COMBINED MODEL

The proposed Combined model for Male' is a multiple linear regression model that uses the available economic and demographic variables which are likely to have an effect on the electricity consumption in Male'. The available variables for Male' are gross domestic product (GDP) and population. The price of electricity remained at the same level for some years before it was changed. This data is not readily available. Therefore, electricity price is not used in this model. These data are obtained from the Ministry of Planning and National Development [MPND, 2004] [MPND, 2003]. Details of the data are given in Appendix A. The relationship between these variables and the electricity consumption in Male' are observed by the respective correlation coefficients. The correlation matrix for the variables is given in Table 7.2.

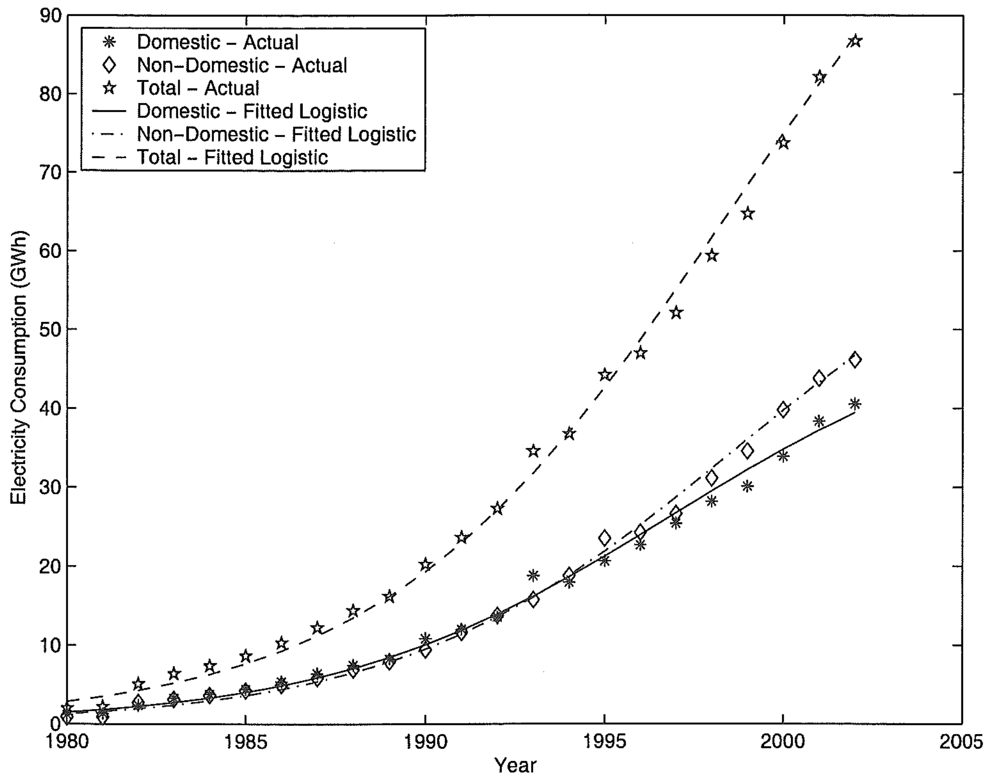

Figure 7.2 Fitted Logistic models for electricity consumption in Male' (Maldives)

Table 7.2 Correlation matrix for the variables of Male'

	Domestic	Non-Domestic	Total	GDP	Population
Domestic	1			0.991	0.968
Non-Domestic		1		0.984	0.952
Total			1	0.988	0.960
GDP				1	0.987
Population					1

The correlation coefficients of GDP and population are high enough to be used in the multiple linear regression model. Therefore, the proposed Combined model is

$$Y = a + b_1 X_1 + b_2 X_2 \tag{7.1}$$

where,

Y is the electricity consumption in GWh
X_1 is GDP (in millions of Rufiyaa),
X_2 is population and
a, b_1 and b_2 are constants.

A validity test that consists of the adjusted coefficient of determination, the F-test and the t-test [Makridakis *et al.*, 1998] for Male' is given in Table 7.3.

Table 7.3 Validity test results for Male'

	adjusted	F- test		t -test		
	r^2	99% value	F	99% value	t_1	t_2
Domestic	0.97	5.78	679	2.52	51.53	-14.03
Non-Domestic	0.96	5.78	599	2.52	61.4	-26.6
Total	0.97	5.78	686	2.52	59.4	-21.9

The adjusted coefficients of determination are high in all cases implying that even in the worst case of the Non-Domestic consumption, 96% of the variance in electricity consumption is explained by the combination of GDP and population for Male'. Therefore, each of those consumption models coupled with a good forecast of GDP and population should produce a good forecast of electricity consumption. The critical values of F for each of the sectors are much lower than the actual F obtained indicating that the Combined models developed using these variables are significant. Similarly, the absolute value of the t- test results t_1 and t_2 for the coefficients of X_1 and X_2 are higher than the critical value of t. This means that each of those coefficients b_1 and b_2 are significantly different from zero. The fitted Combined models for the Domestic and the Non-Domestic sectors and the Total consumption are shown in Figure 7.3. The corresponding MAPE values are 22.3, 33.1 and 27.0 for the Domestic and the Non-Domestic sectors, and the Total electricity consumption respectively. These model fits are worse than the Logistic model fits.

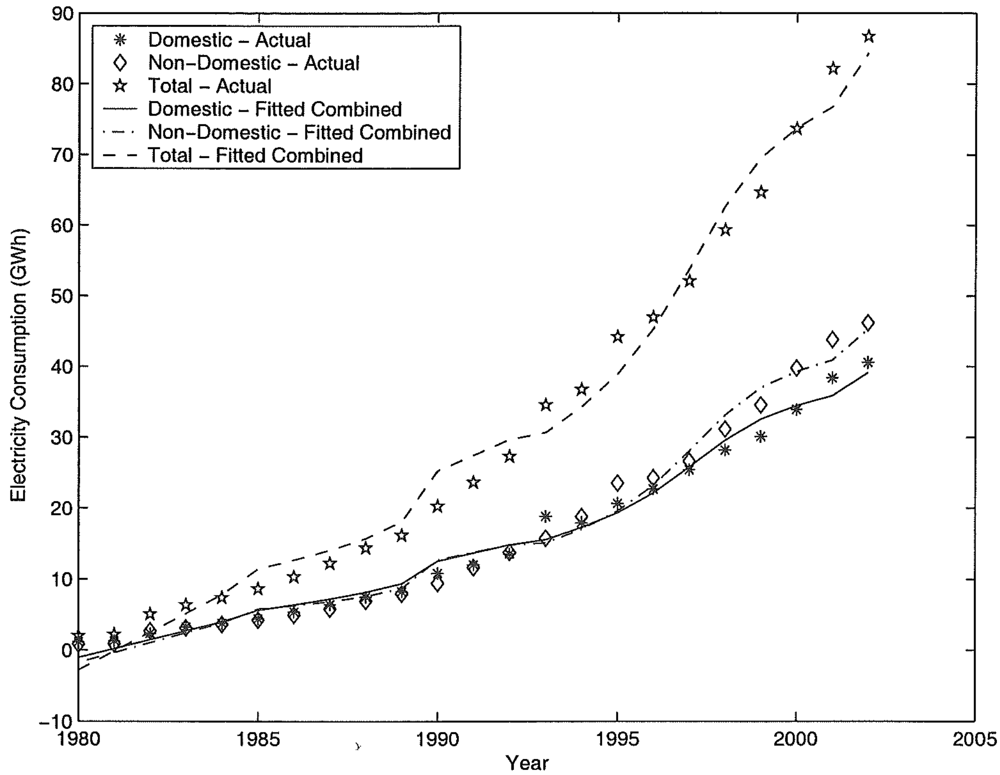

Figure 7.3 Fitted Combined models for electricity consumption in Male' (Maldives)

Figure 7.4 shows the residuals produced by the Combined model against the fitted values and the variables used in the model. The residuals show no apparent pattern. This indicates that the residuals produced by the model are independent. Therefore, the Combined model will be used for forecasting electricity consumption in the Maldives.

7.5 HARVEY LOGISTIC AND HARVEY MODELS

Application of the Harvey Logistic model to the electricity consumption data of Male' resulted in the following models.

Domestic: $$\ln y_t = 2\ln Y_{t-1} + 430.1 - 0.218t \qquad (7.2)$$

Non-Domestic: $\ln y_t = 2\ln Y_{t-1} + 434.4 - 0.220t$ (7.3)

Total: $\ln y_t = 2\ln Y_{t-1} + 436.1 - 0.222t$ (7.4)

The resulting Harvey models are

Domestic: $\ln y_t = 0.29\ln Y_{t-1} - 103.4 + 0.052t$ (7.5)

Non-Domestic: $\ln y_t = 0.34\ln Y_{t-1} - 135.8 + 0.068t$ (7.6)

Total: $\ln y_t = 0.36\ln Y_{t-1} - 135.8 + 0.049t$ (7.7)

In both cases, t is the time in years from 1980.

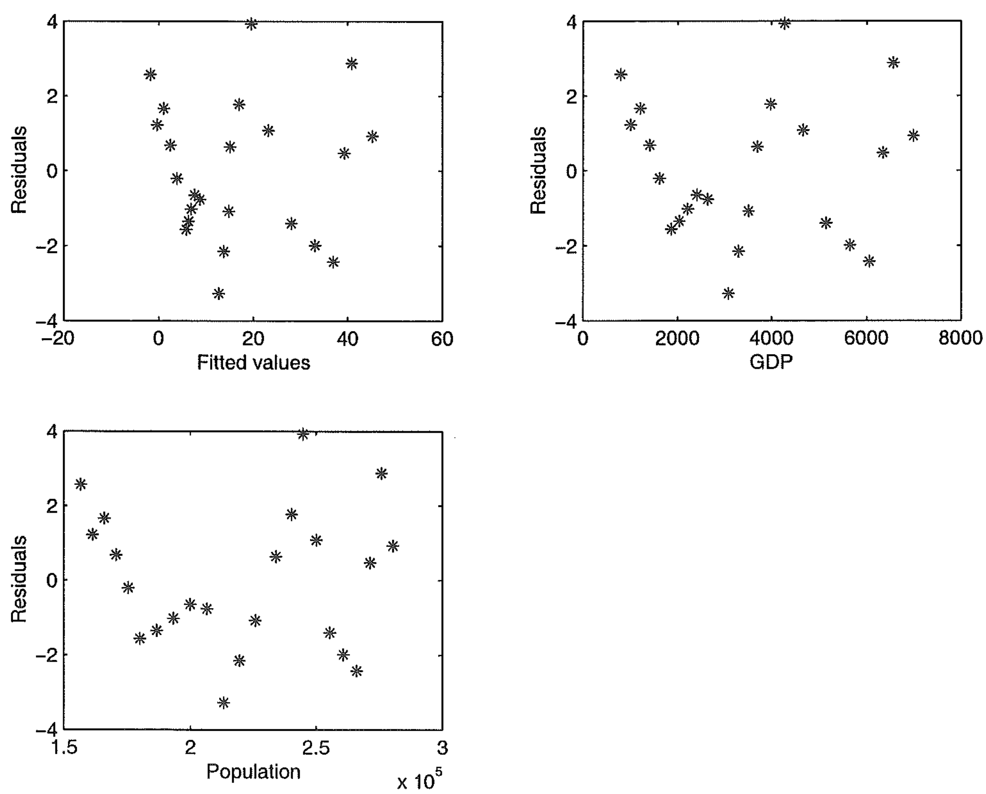

Figure 7.4 Residuals against the fitted values and variables for Male'

Although similar in model form, these two models have produced quite different coefficients. This suggests retaining both the models for forecasting. The fitted Harvey Logistic and Harvey models for the Domestic, Non-Domestic and Total consumption are shown in Figure 7.5 and Figure 7.6 respectively.

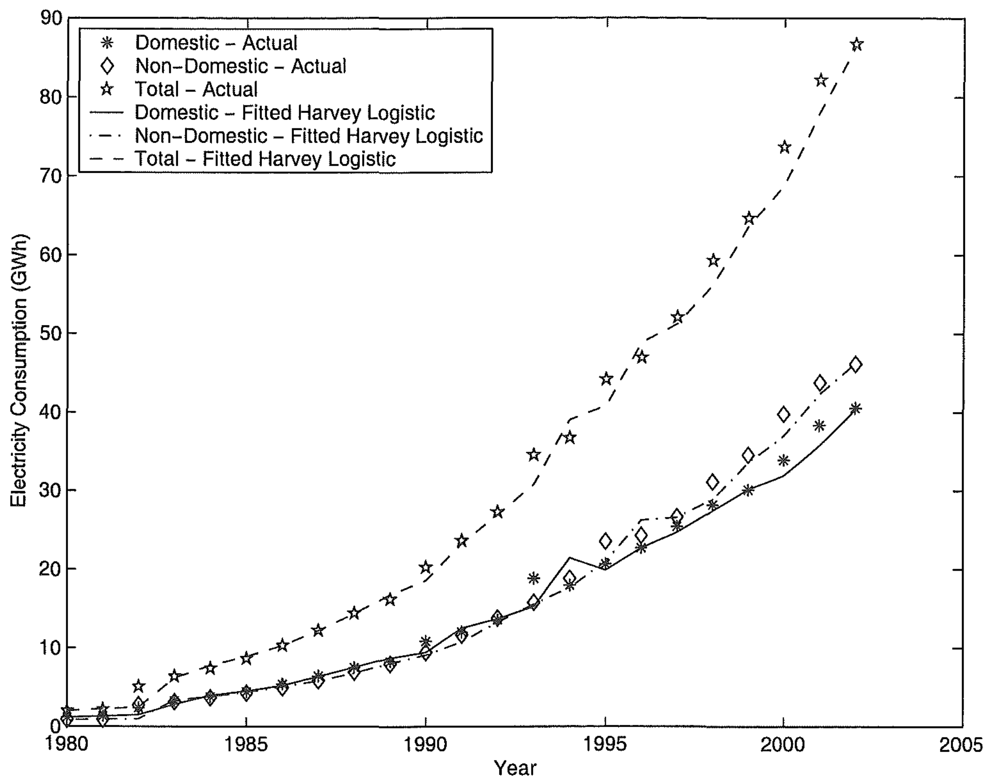

Figure 7.5 Fitted Harvey Logistic models for Male' (Maldives)

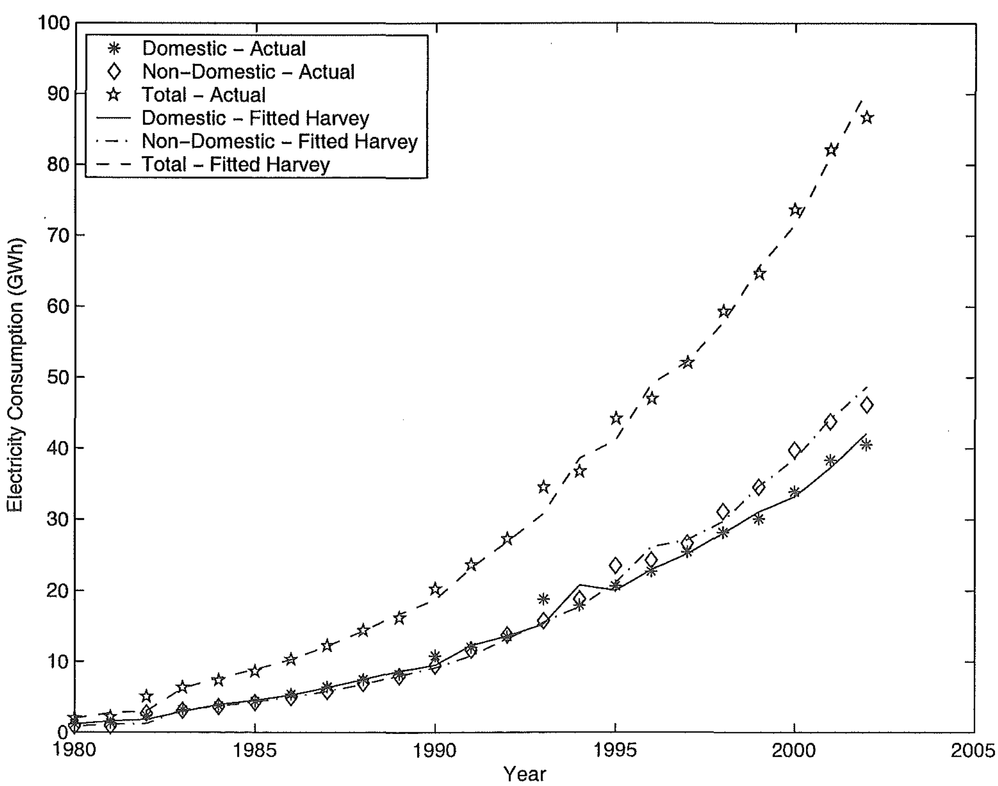

Figure 7.6 Fitted Harvey models for Male' (Maldives)

The MAPE values of the fitted Harvey Logistic models are 7.4, 7.6 and 5.7 for the Domestic, Non-Domestic and Total consumption respectively. The MAPE values for the fitted Harvey models are 6.0, 6.6 and 5.7 respectively. These indicate that these two models have resulted in very similar fits of the actual data. The corresponding DW values for the Harvey Logistic models fits are 2.5, 1.5 and 1.8 for the Domestic, the Non-Domestic and the Total electricity consumption respectively while those for the Harvey models are 3, 1.8 and 2.5 respectively. Although there is some indication of correlation in the Harvey model for the Domestic sector, all the other DW values are generally close to the desired value of 2, indicating that the residuals produced by these models are white noise. Therefore these models are accepted for forecasting electricity consumption in Male', Maldives.

7.6 ARIMA MODELS

7.6.1 ARIMA Model for the Domestic Sector

The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the Domestic electricity consumption in Male' are shown in Figure 7.7. The $\pm 1.96/\sqrt{n}$ bounds for the ACF and PACF are shown by the dotted lines. A significant amount of autocorrelations are outside the limits indicating non-stationary. The first partial autocorrelation coefficient is very dominant and close to 1, also indicating non-stationary. The data is thus differenced at lag 1. The resulting ACF and PACF plots of the differenced data are shown in Figure 7.8.

The ACF and PACF of the differenced data are all well within the bounds of stationary. Using the software ITSM2000 [Brockwell and Davis, 2002], the best model is identified based on the AICC criteria. The best model for the Domestic sector is ARIMA(1,1,2). The maximum likelihood of the model is

$$Y_t' = 0.758Y_{t-1} + e_t - 0.983e_{t-1} + 0.703e_{t-2} \tag{7.8}$$

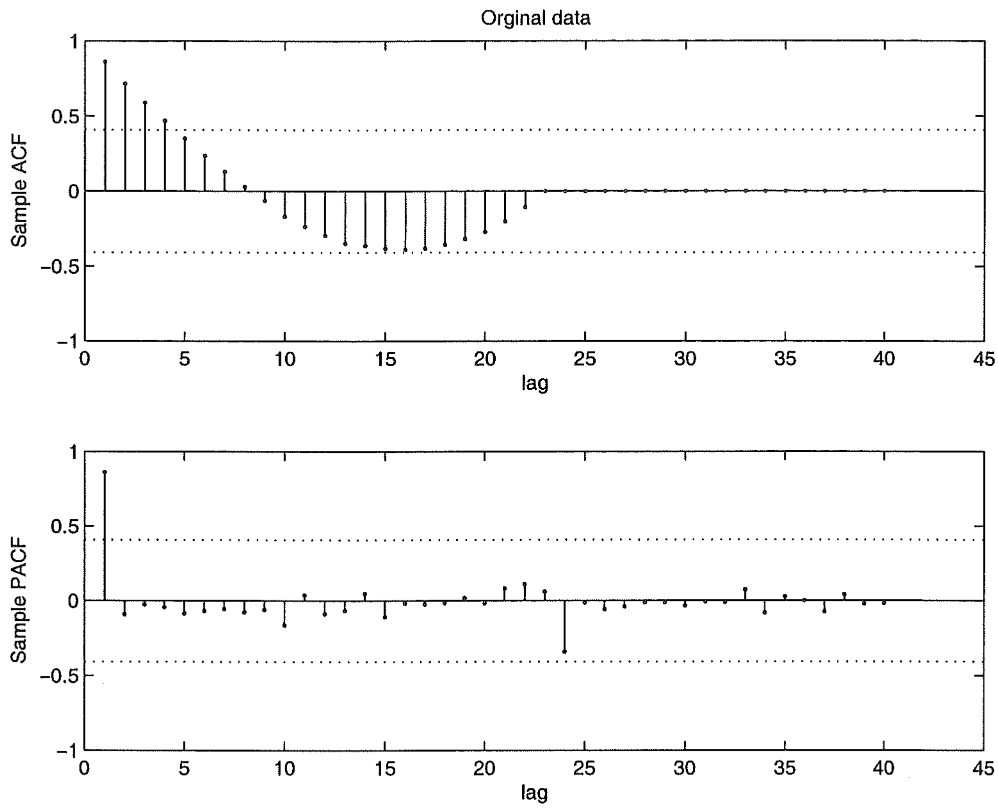

Figure 7.7 ACF and PACF of original Domestic consumption data

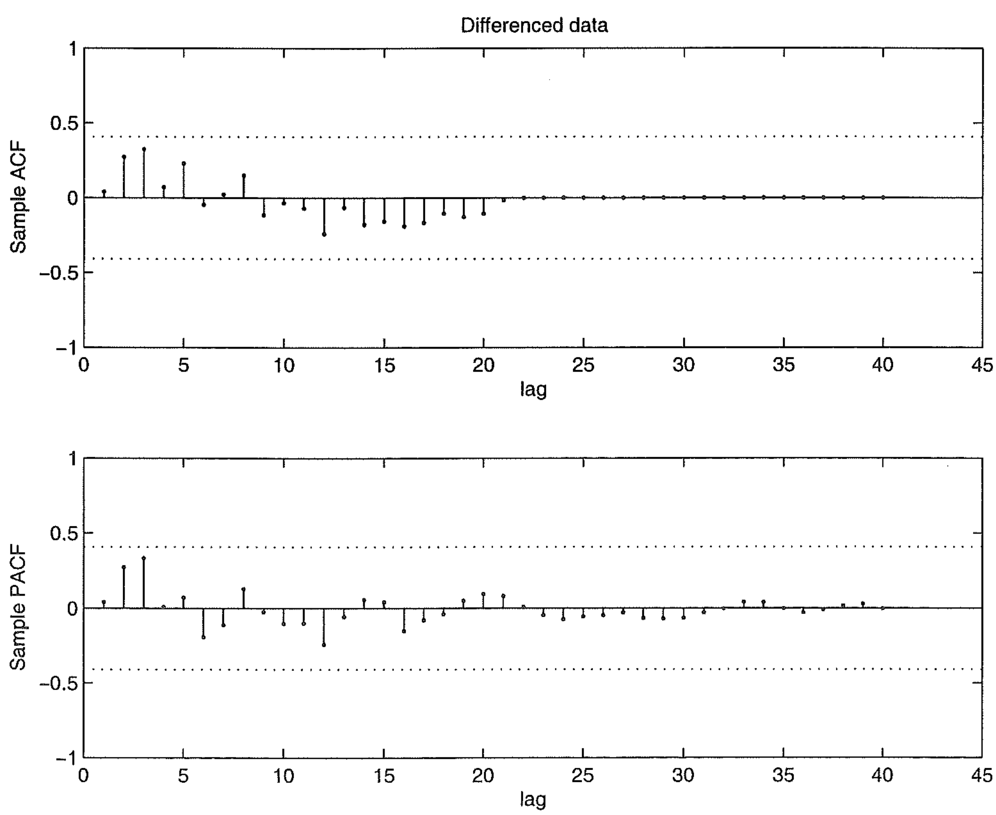

Figure 7.8 ACF and PACF of differenced data for the Domestic sector

where e_t is approximated by a zero mean white noise (WN) sequence, i.e. e_t ~ WN(0, 1.28).

Since the data is differenced and mean corrected before estimation, $Y_t' = Y_t - Y_{t-1} - 1.79$ and thus

$$Y_t = 1.791 + 1.758Y_{t-1} + e_t - 0.983e_{t-1} + 0.703e_{t-2} \quad (7.9)$$

The fit by the ARIMA(1,1,2) model for the Domestic sector is shown in Figure 7.9.

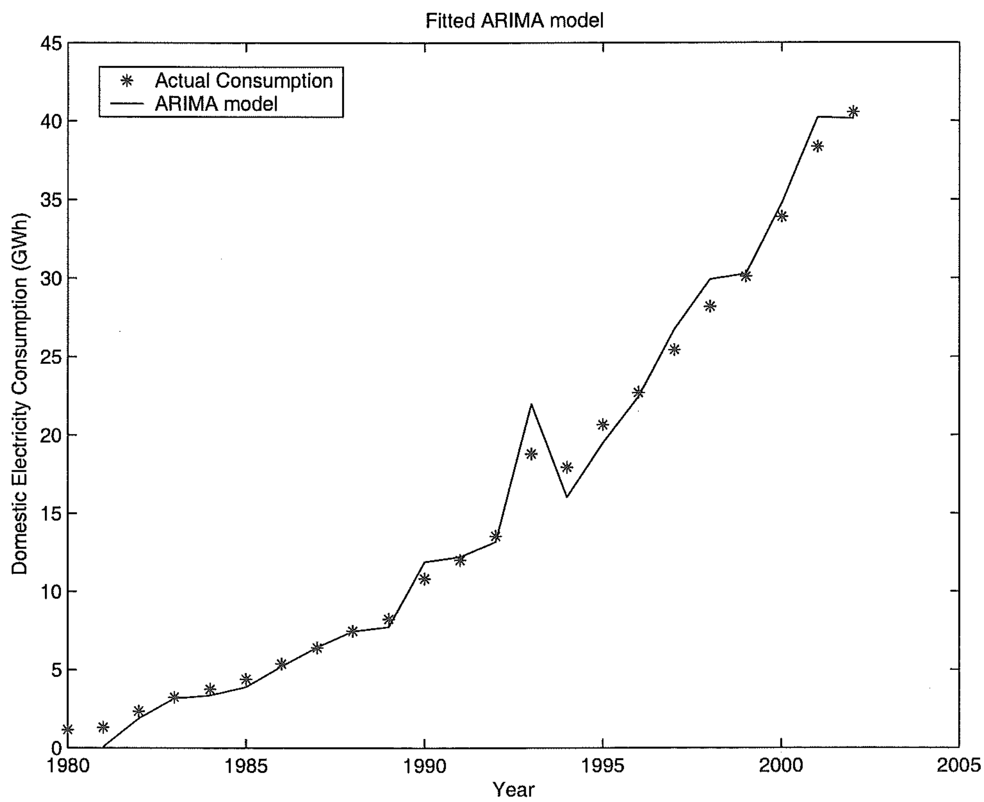

Figure 7.9 Fitted ARIMA(1,1,2) model for the Domestic sector (MAPE = 9.9)

The ARIMA(1,1,2) model has produced a good fit of the historical data. The dependency of the ARIMA models on the historical data is shown by the sudden jump in the year 1993, when the actual consumption is also very high. Figure 7.10 shows the ACF and PACF of the residuals produced by the model. The coefficients of the residuals are well within the required bounds of $\pm 1.96/\sqrt{n}$ in all instances. Therefore, it can be concluded that the residuals produced by this model constitute white noise. In addition, the Ljung-Box Q statistic [Brockwell and Davis, 2002] for lags h = 15 was also carried out. In the case of New Zealand, a lag of 20 was used where the number of data points available was 57. However, a lag of 20 cannot be used for Male' as the number of available consumption data points is 23. Attempting to use a lag of 20 for Male' terminates the software ITSM2000 [Brockwell and Davis, 2002]. The results of the Ljung-Box Q statistic for Male is 7.44. This is much lower than the critical chi-square value of 25.0. This indicates that the correlations in the residuals are not significant and therefore it can be concluded that the residuals are white noise. Thus, the ARIMA(1,1,2) model is used to forecast the Domestic electricity consumption in Male'.

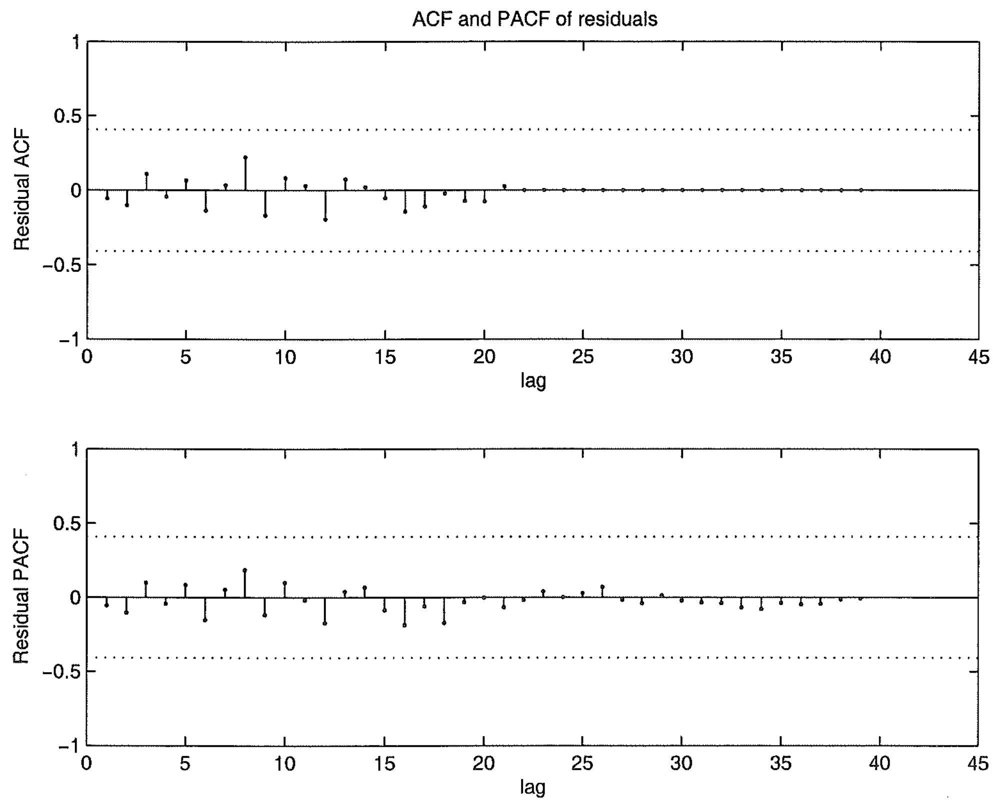

Figure 7.10 ACF and PACF of the residuals for the Domestic sector

7.6.2 ARIMA Model for the Non-Domestic Sector

The ACF and PACF plots of the Non-Domestic consumption for Male' are shown in Figure 7.11.

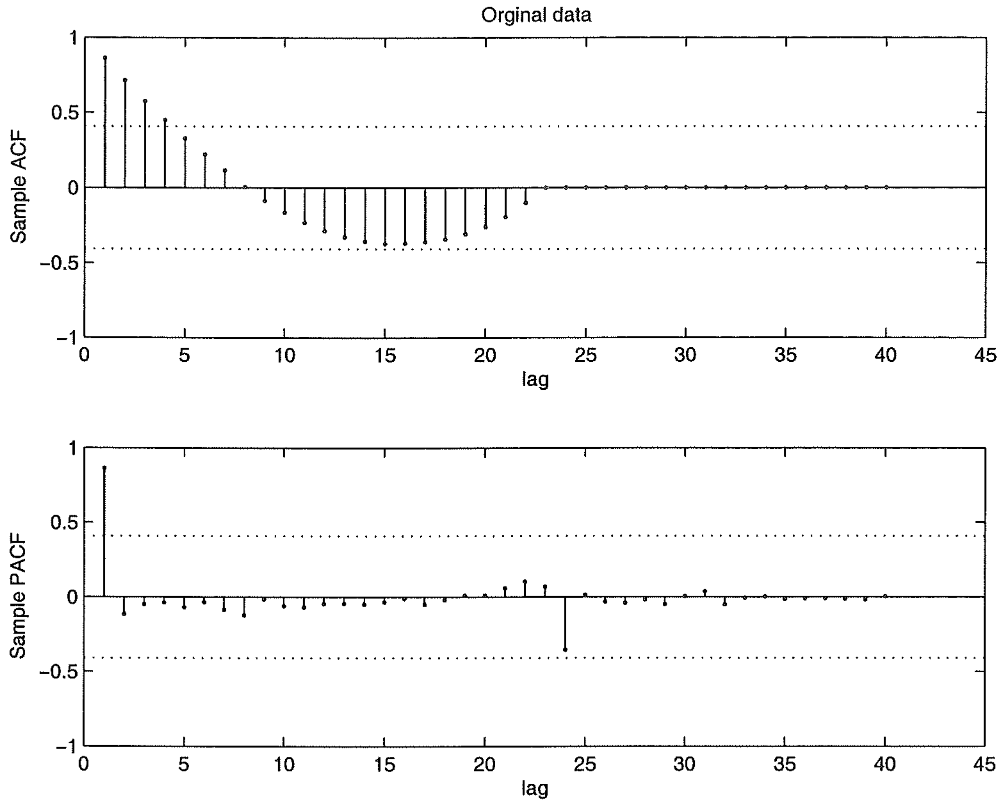

Figure 7.11 ACF and PACF of the original Non-Domestic consumption

The ACF and PACF plots of the original data are very similar to that for the Domestic sector. A significant amount of autocorrelations are outside the required bounds indicating non-stationarity. The first partial autocorrelation coefficient is very dominant and close to 1, also indicating non-stationarity. The data is thus differenced at lag 1. The resulting ACF and PACF plots of the differenced data shown in Figure 7.12 indicate that stationary is still not achieved. Thus data is differenced a second time and the resulting plots are shown in Figure 7.13. The series is now stationary. The best model for the Non-Domestic sector is again obtained using the AICC criteria and the software ITSM2000 [Brockwell and Davis, 2002]. The best model selected is ARIMA(0,2,1) model. The maximum likelihood estimation of the model is

$$Y_t'' = e_t - 0.812e_{t-1} \qquad (7.10)$$

where e_t is approximated by a zero mean white noise (WN) sequence, i.e. e_t ~ WN(0, 1.16).

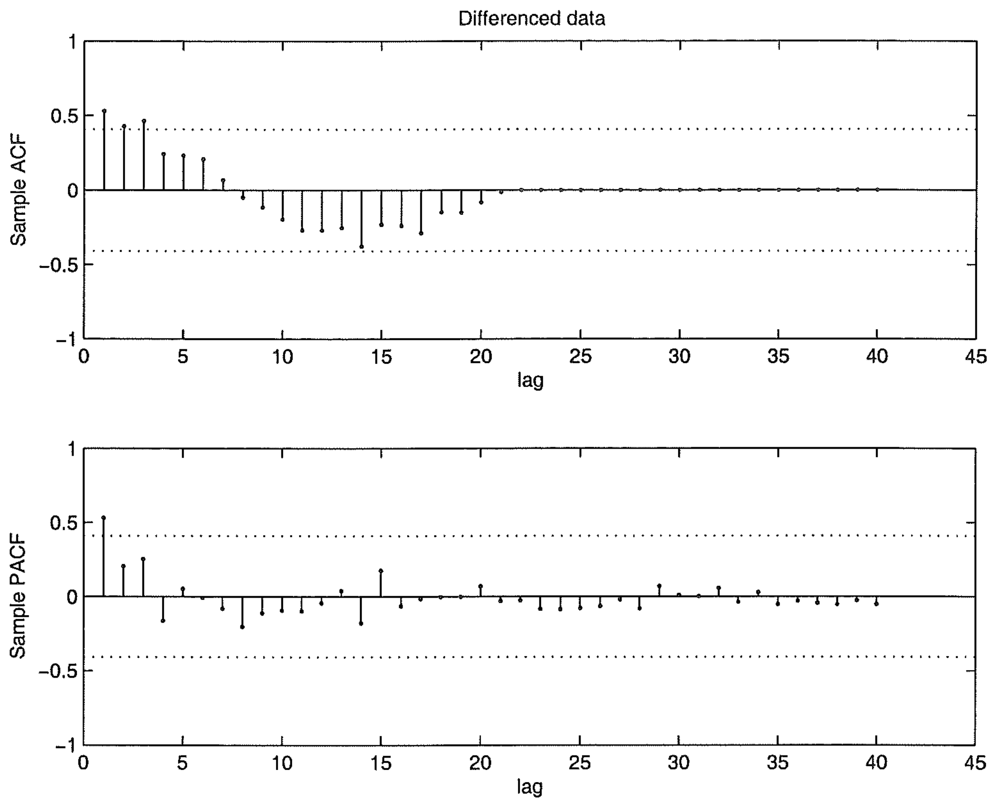

Figure 7.12 ACF and PACF of first differenced Non-Domestic data

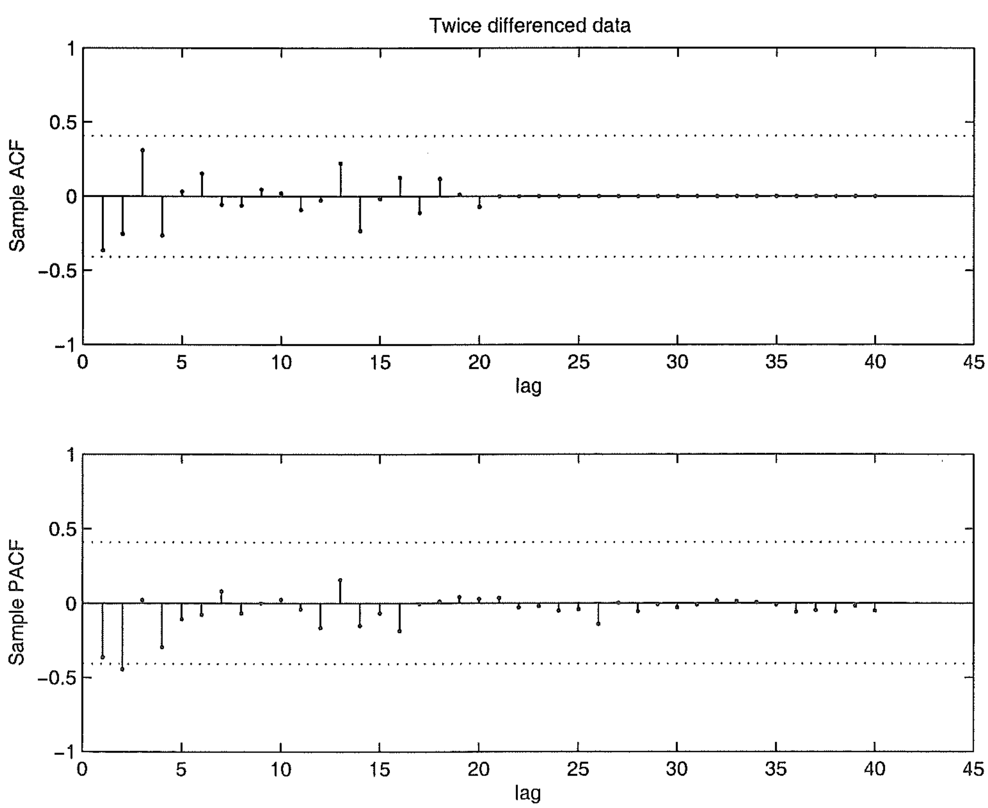

Figure 7.13 ACF and PACF of twice differenced data (Non-Domestic sector)

Since the data is differenced twice and mean corrected before estimation, $Y_t'' = Y_t - 2Y_{t-1} + Y_{t-2} - 0.111$ and thus

$$Y_t = 0.111 + 2Y_{t-1} - Y_{t-2} + e_t - 0.812e_{t-1} \tag{7.11}$$

Figure 7.14 shows the fit of the historical Non-Domestic consumption obtained by the ARIMA (0,2,1) model. The ARIMA(0,2,1) has obtained a better estimate of the Non-Domestic sector than the ARIMA model of the Domestic sector with a lower MAPE value of 7.3 as compared to 9.9 in the Domestic sector.

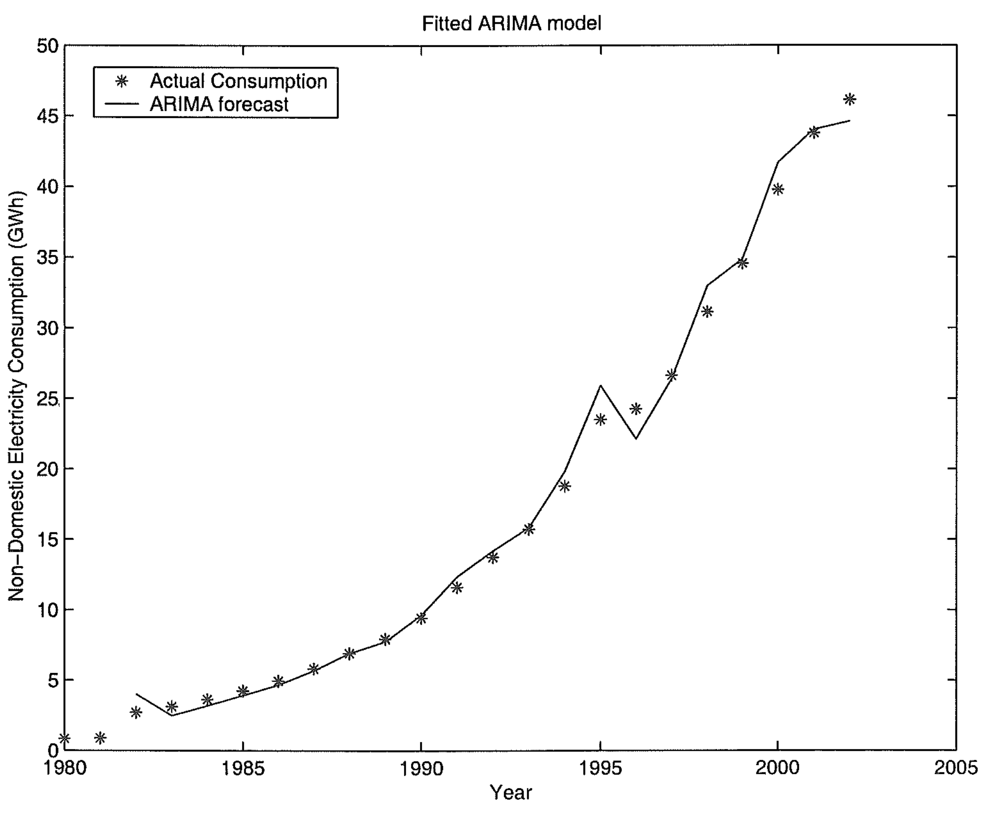

Figure 7.14 Fitted ARIMA(0,2,1) model estimates for the Non-Domestic sector (MAPE = 7.3)

The ACF and PACF of residuals produced by this model are shown in Figure 7.15. The residuals are well within the required limits for stationarity. This indicates that the residuals can be considered as a white noise series. The result of the Ljung-Box Q statistic is 11.77. This is much smaller than the critical chi-squared value of 25.0. This indicates that the correlations in the residuals are not significant and therefore it can be concluded that the data is white noise. This analysis has strengthened the choice of the

ARIMA(0,2,1) model to forecast the Non-Domestic electricity consumption in the Maldives.

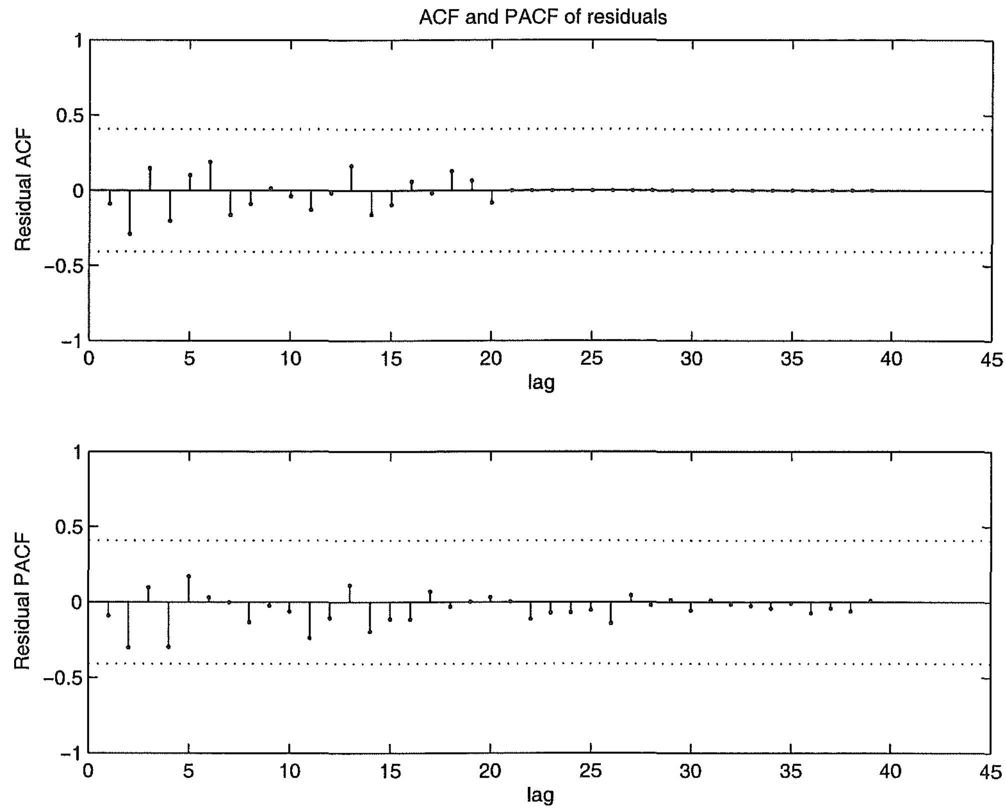

Figure 7.15 ACF and PACF of the ARIMA(0,2,1) model for Non-Domestic sector

7.6.3 ARIMA Model for the Total Consumption

The ACF and PACF of the original Total consumption shown in Figure 7.16 indicate non-stationarity as a significant number of correlations are outside the required bounds. The ACF and PACF plots of the first differenced data (Figure 7.17) also indicate that some correlations are outside the limits and a second differencing would help to achieve stationarity. Figure 7.18 shows the plots of the second differenced data. All correlations except one in each of the ACF and PACF plots are now well within the limits of stationarity. The best model obtained for the Total consumption is ARIMA(2,2,0) model.

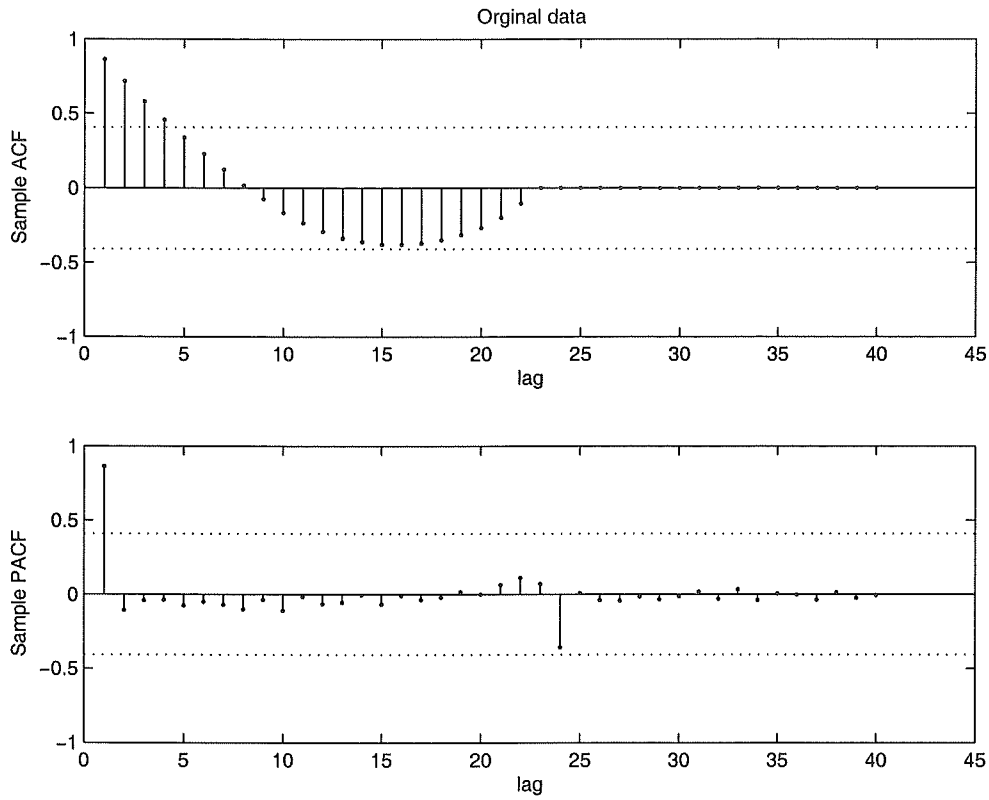

Figure 7.16 ACF and PACF of the original Total consumption data

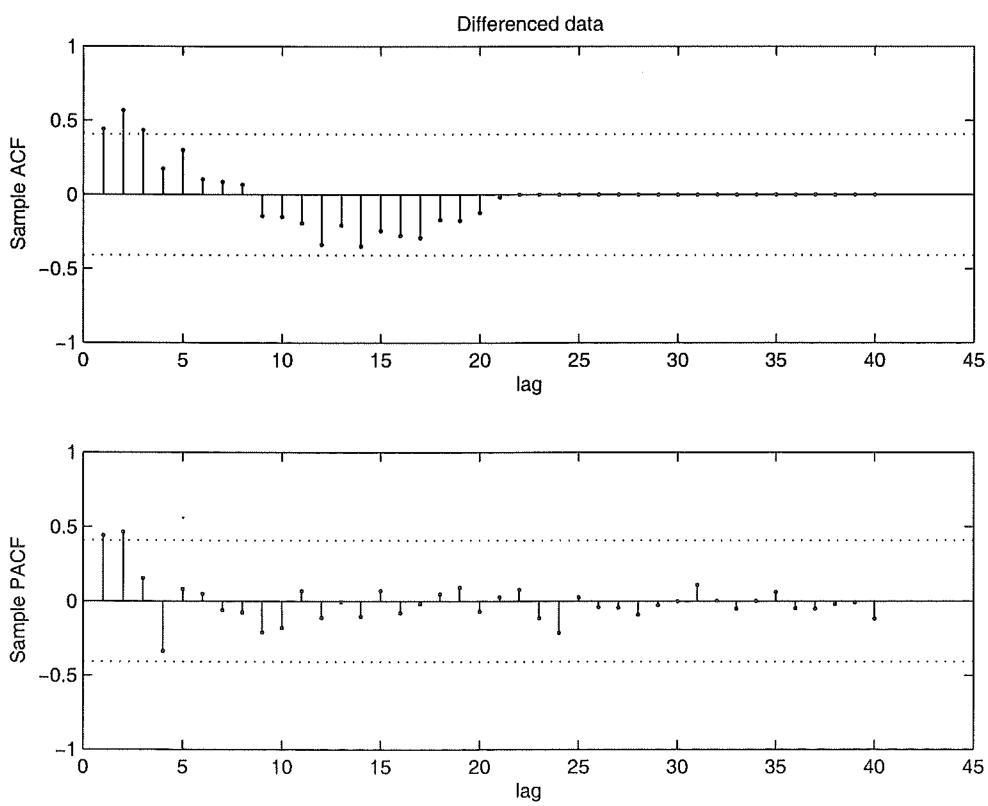

Figure 7.17 ACF and PACF of the first differenced Total consumption data

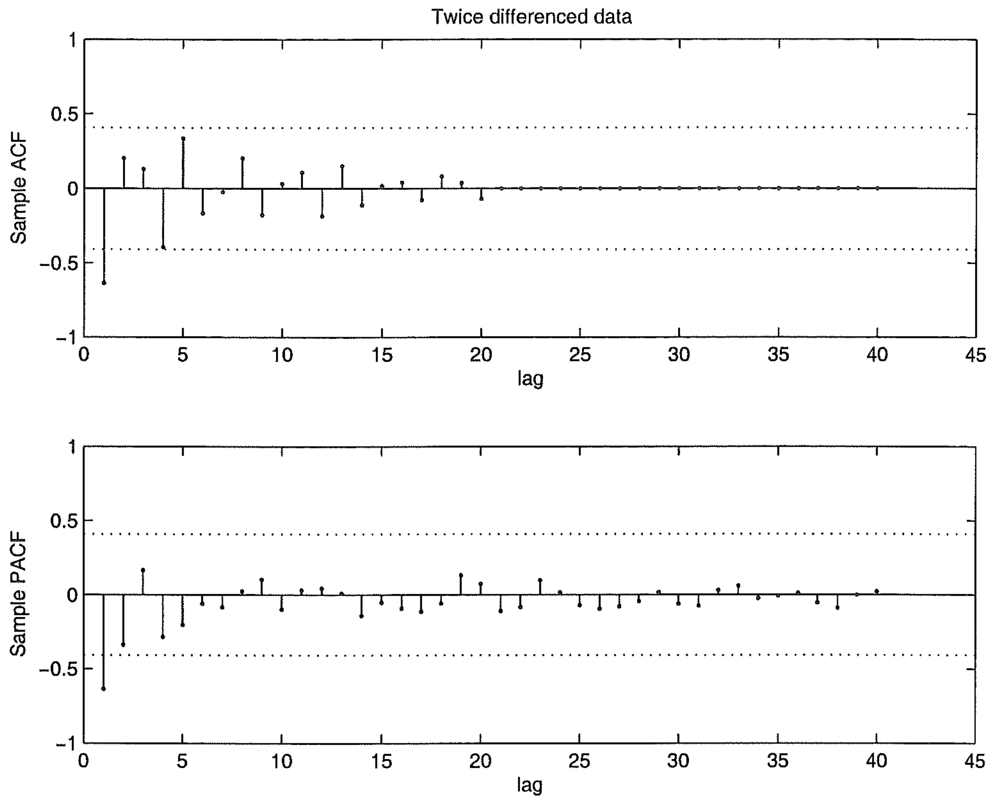

Figure 7.18 ACF and PACF of twice differenced Total consumption data

The maximum likelihood estimate of the ARIMA(2,2,0) model is

$$Y_t'' = 1.237Y_{t-1} - 0.671Y_{t-2} + e_t \qquad (7.12)$$

where e_t is approximated by a zero mean white noise (WN) sequence, i.e. e_t ~WN(0, 2.18).

Since the data is differenced twice and mean corrected before estimation, $Y_t'' = Y_t - 2Y_{t-1} + Y_{t-2} - 0.207$ and thus

$$Y_t = 0.207 + 2.237Y_{t-1} - 1.671Y_{t-2} + e_t \qquad (7.13)$$

The fit of the ARIMA(2,2,0) model to the Total consumption is shown in Figure 7.19. The corresponding ACF and PACF of the residuals produced by the ARIMA(2,2,0) model are shown in Figure 7.20.

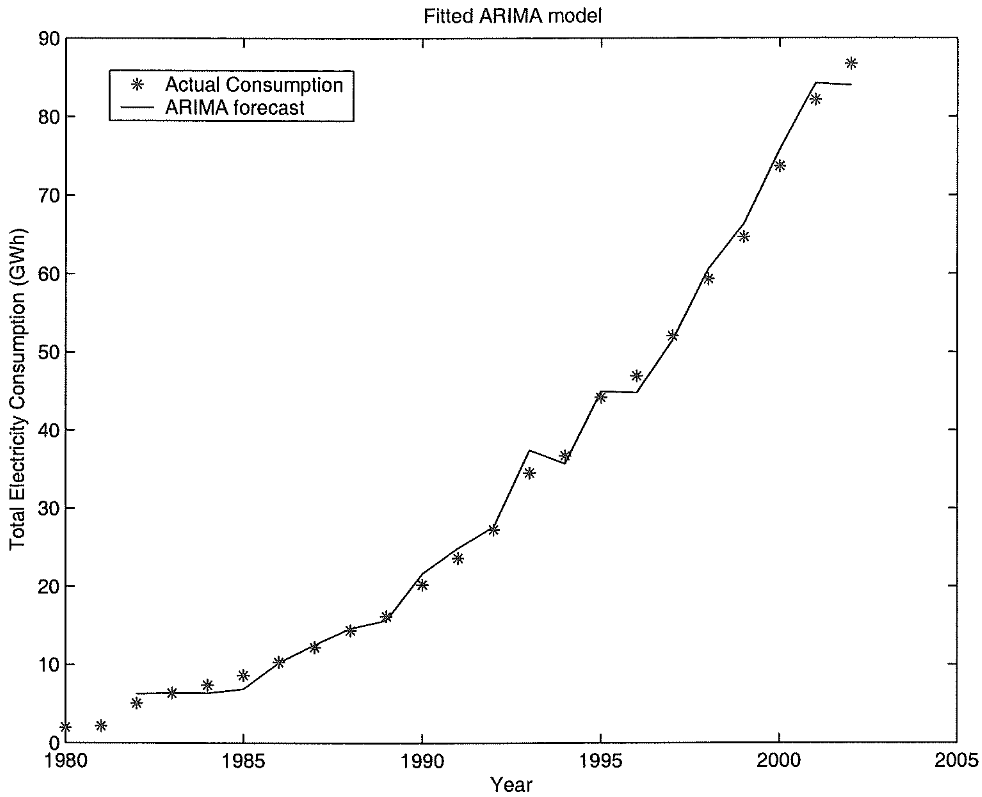

Figure 7.19 Fitted ARIMA (2,2,0) for the Total electricity consumption (MAPE = 5.4)

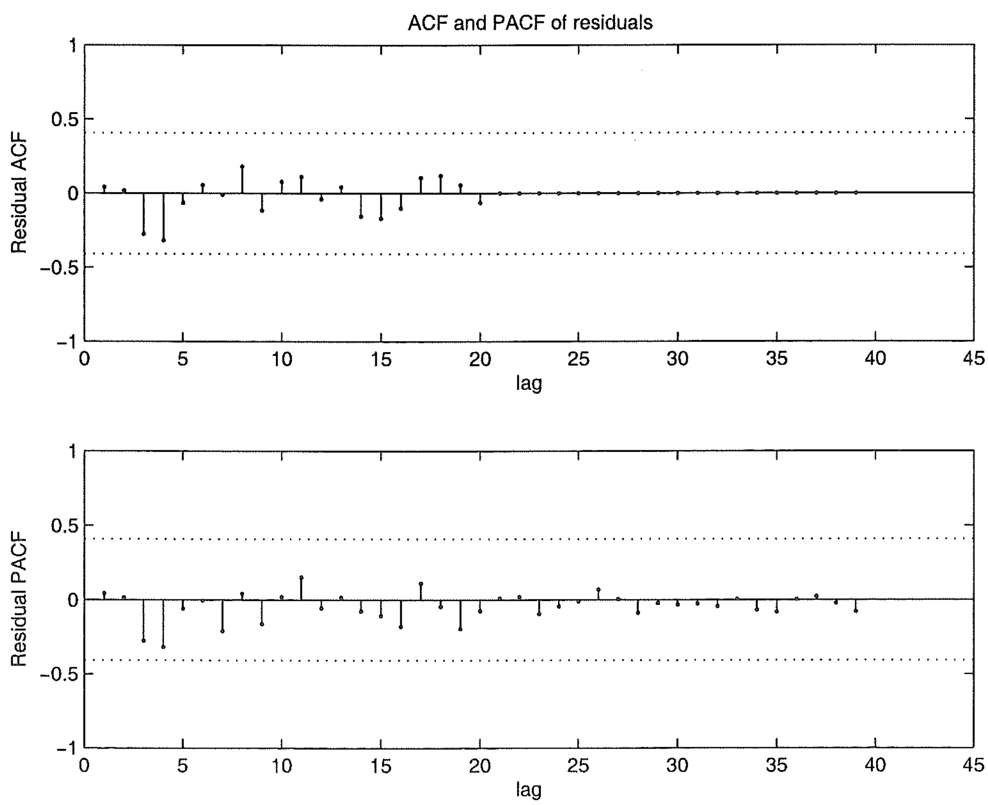

Figure 7.20 ACF and PACF of the residuals produced by the ARIMA(2,2,0) for Total consumption

It can be seen that this model has resulted in an even better fit of the historical Total electricity consumption with a MAPE value of 5.4, when compared with the Domestic and the Non-Domestic sector. In the ACF and PACF plots, all the coefficients are well within the required bounds and therefore can be considered stationary. In addition, the result of the Ljung-Box Q statistic is 11.93. This is much smaller than the critical chi-squared value of 25.0. This indicates that the correlations in the residuals are not significant and therefore it can be concluded that the data is white noise. Therefore, the chosen ARIMA(2,2,0) model can be used to forecast the Total electricity consumption in Male' .

7.7 APPLICATION OF THE VAL MODEL TO MALE'

The asymptotic levels are initially obtained by the Fibonacci search technique as for New Zealand. As the number of data points available for Male' is much smaller than New Zealand, the asymptotes are initially estimated from 1993 to 2002 for a period of 10 years. The resulting asymptotes are then estimated using the GDP and population of the Maldives. The asymptotes and their estimates for the Domestic, the Non-Domestic and the Total consumption of Male' are shown in Figure 7.21 to 7.23 respectively.

The saturation levels in the Domestic and the Non-Domestic sectors are decreasing. However, the saturation levels and their estimates in the Total consumption are increasing. This is indicating that the Domestic and Non-Domestic sectors are not mature enough for the Fibonacci search technique to be applied effectively. The main reason being that the number of data points available is limited (from 1980 to 1992) when processing the saturation level for the year 1992 and so on for the consecutive years. This has resulted in inconsistency in the saturation levels obtained. An attempt to continue with these unstable saturation levels resulted in further instability in the VAL models except for the Total consumption. The forecasts for the Total consumption, along with the original Logistic model and actual data are shown in Figure 7.24.

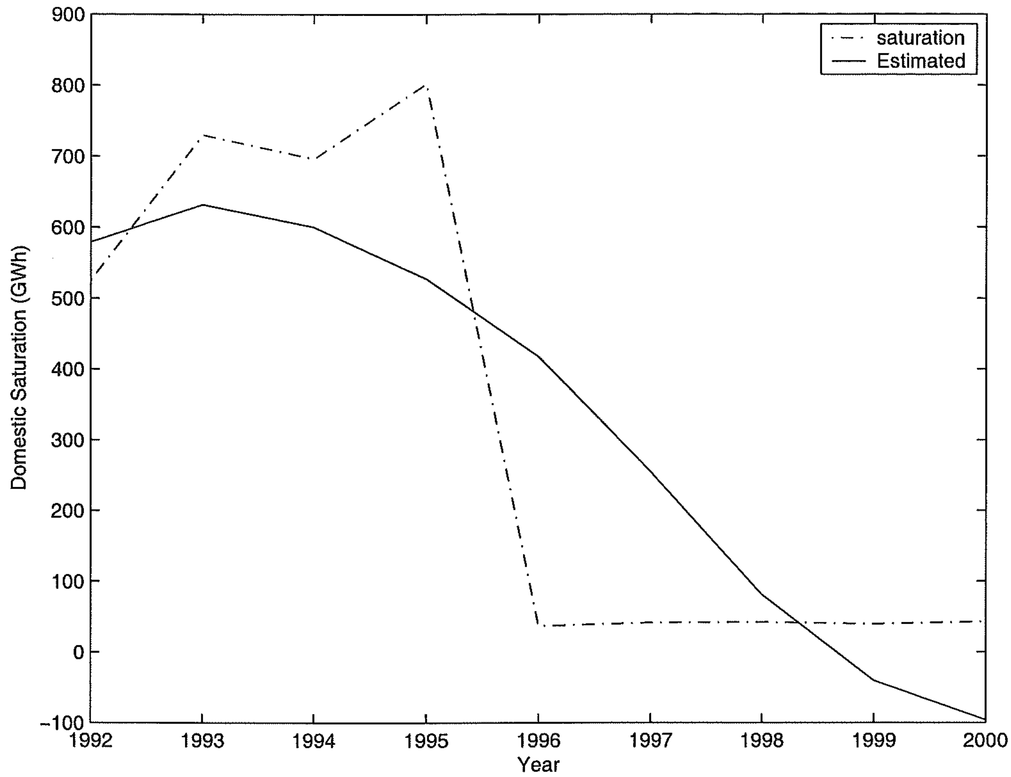

Figure 7.21 Estimated saturation levels of the Domestic sector

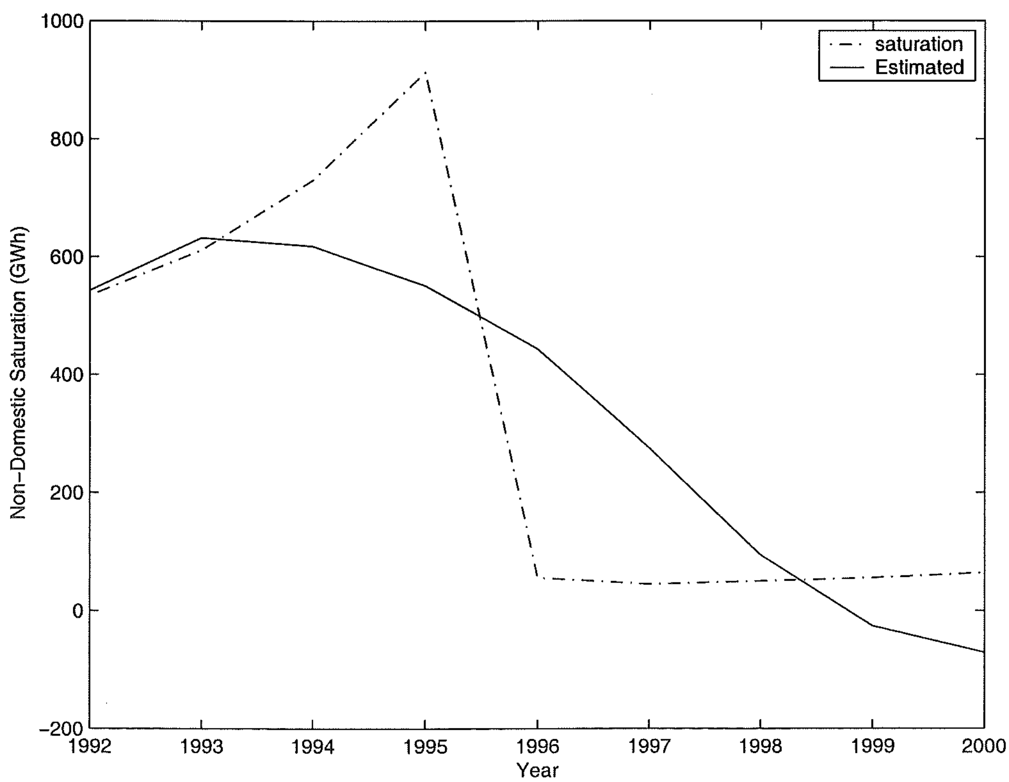

Figure 7.22 Estimated saturation levels of the Non-Domestic sector

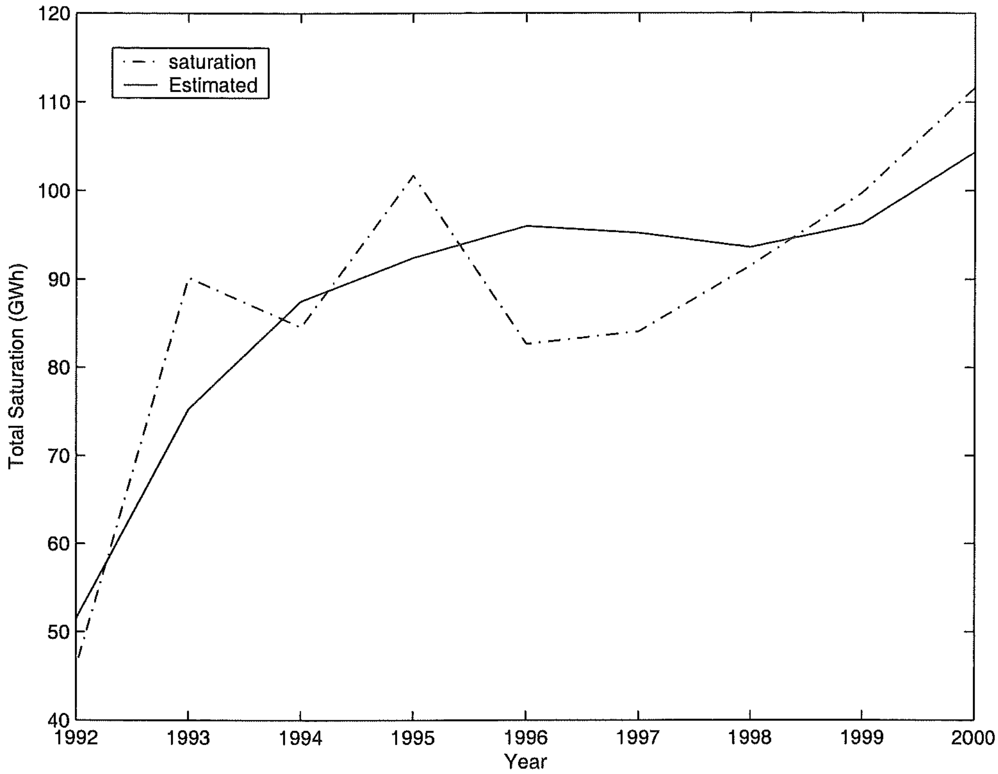

Figure 7.23 Estimated saturation levels for the Total consumption

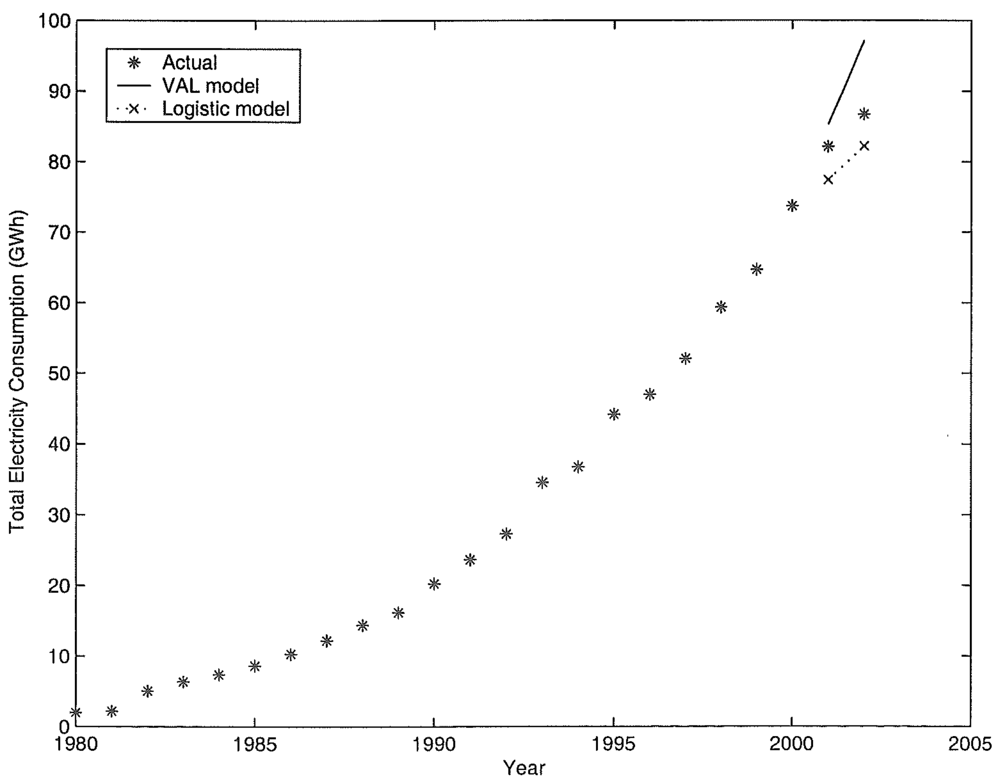

Figure 7.24 Forecasts of the VAL and Logistic models along with the actual data

The forecasts for this particular situation show that the VAL model has not significantly resulted in improved forecasts. Therefore, it is decided not to use the VAL model for electricity consumption in Male'. This does not mean that the VAL model will not be applicable for Male' in the future. The main reason for the instability of the VAL model for Male' is the few data points available for modelling. Unlike other models, the VAL models require more data points to obtain initial estimates of the saturation levels by the Fibonacci search technique. As some inconclusive results are currently obtained for the Total electricity consumption, it is quite reasonable to assume that as more data points are available in the future, the VAL model could lead to a stable and hopefully a very competitive model for forecasting electricity consumption in Male'.

7.8 COMPARISON OF MODEL FIT AND FORECASTING ACCURACY

Forecasting accuracies of the five developed models for electricity consumption in Male' are compared. As for New Zealand, forecasting accuracy is measured using MAPE. However, forecasting accuracy is measured over a five year period as the number of available data points to develop models is very small and discarding large amount of data for accuracy comparison may result in unstable models. Forecasting accuracy for the five year ahead forecast is measured by discarding the last five years of consumption data (from 1998 to 2002). Thus, models are developed using data from 1980 to 1997. In the case of the Combined model, the GDP and population data up to the year 1997 are used. Forecasting accuracies from the one year ahead to five years ahead are shown in Figure 7.24 for the five models for all data sets.

In comparing the forecasting accuracy, the five year period is divided into short term (1-3 years) and medium term (4-5 years) forecasts. The models are ranked from 1 to 5 (1= best model, 5 = worst model). The ranking of the models in terms of the model fit and forecasting accuracy in the Domestic, the Non-Domestic and the Total consumption are given in Table 7.4.

The best model fit of the historical data is given by the Harvey model for the Domestic and the Non-Domestic sectors and by the ARIMA model for the Total consumption. In general the worst model fit is given by the Combined model in all cases. The Harvey Logistic model gave the best fit for the Non-Domestic sector.

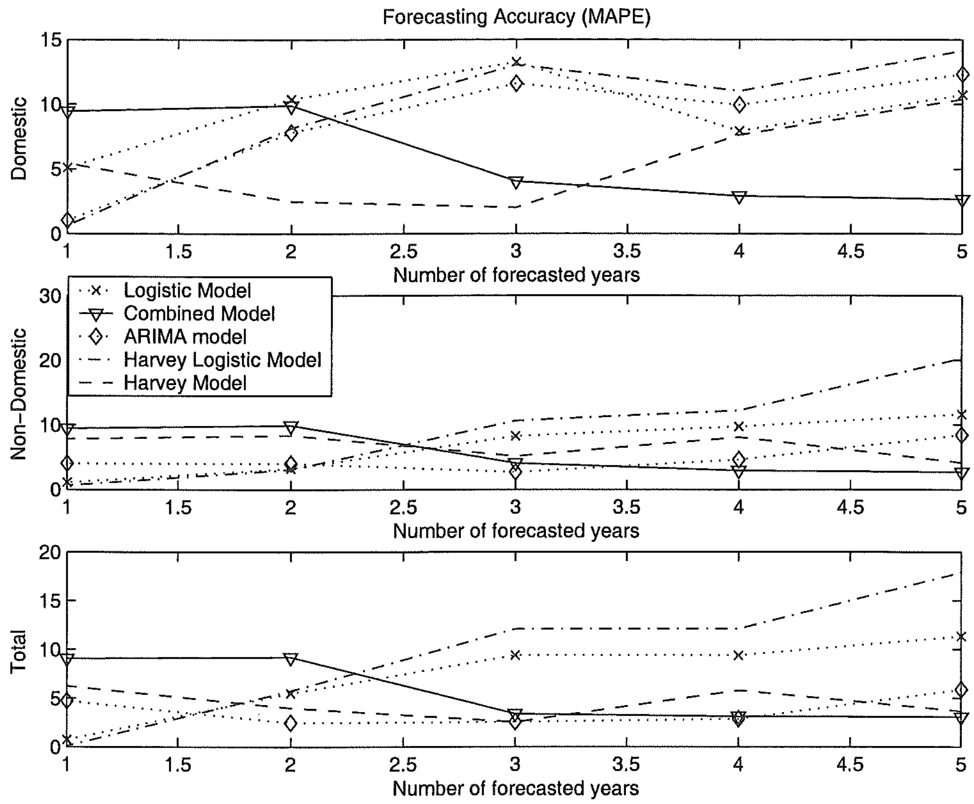

Figure 7.25 Forecasting accuracies of the developed models for Male'

Table 7.4 Rankings of models in terms of model fit and forecasting accuracy (1 = best model, 5 = worst model)

Model	Domestic				Non-Domestic				Total			
		Forecast accuracy				Forecast accuracy				Forecast accuracy		
	fit	Short	medium	**Overall**	fit	Short	medium	**Overall**	fit	Short	medium	**Overall**
Logistic	4	5	3	**5**	4	2	4	**4**	4	3	4	**4**
Combined	5	3	1	**2**	5	4	1	**2**	5	5	1	**3**
ARIMA	3	2	4	**3**	3	1	3	**1**	1	1	2	**1**
Harvey Logistic	2	4	5	**4**	1	3	5	**5**	2	4	5	**5**
Harvey	1	1	2	**1**	1	5	2	**3**	2	2	3	**2**

In the Domestic sector, the best short term forecast is given by the Harvey model. The best medium term forecast is given by the Combined model. The Harvey model is also ranked the second best in forecasting medium term Domestic consumption while the ARIMA model is ranked as the second best in the short term. The worst forecasts in the Domestic sector are given by the Logistic and Harvey Logistic models. In general, the best model to forecast the Domestic electricity consumption in Male' is the Harvey model, while the overall second best forecasts are given by the Combined model.

In the Non-Domestic sector, the best short term forecast is given by the ARIMA model and the best medium term forecast is given by the Combined model. The second best Non-Domestic forecast is given by the Logistic model for the short term and by the Harvey model for the medium term. Overall, the worst forecasts are given by the Harvey Logistic model. The best overall forecasts are given by the ARIMA model and the second best forecasts are given by the Combined model.

In the Total consumption, the best short term forecast is given by the ARIMA model and the best medium term forecast by the Combined model. The second best forecasts are given by the Harvey model for the short term and ARIMA model for the medium term. Once again the worst overall Total consumption forecasts are given by the Harvey Logistic model. The best overall forecasts are given by the ARIMA model and the second best by the Harvey model.

In summary, the best models to forecast electricity consumption in Male' are the Harvey model for the Domestic sector and the ARIMA model for the Non-Domestic sector and the Total consumption. Although the best or second best model fit is given by the Harvey Logistic model, it has generally given rise to the worst forecasts. The Harvey model remained at a consistent level of best or second best in model fit and forecasting accuracy. The ARIMA model also maintained a moderate level of model fit and was the best in forecasting accuracy. The Combined model gave the worst model fits but gave moderate levels of forecasting accuracy. In general, the best models to forecast electricity consumption in Male' are ARIMA, Harvey and Combined models.

7.9 COMPARISON OF FORECASTS

The forecasts obtained by the developed models from 2003 to 2012 are now compared. For the Maldives, a fifteen year forecast as for New Zealand is not projected due to the few historical data points available to develop the models. Figures 7.26 to 7.28 show the forecasts obtained by the applied models for the Domestic and the Non-Domestic sectors and the Total consumption respectively. For the Domestic sector, the Harvey model has given rise to the highest forecasts while the Logistic and Harvey Logistic has given rise to the lowest forecasts. The forecasts by the Combined and ARIMA models are in the middle. The forecasts for the Non-Domestic sector and the Total consumption follow the same pattern as the Domestic sector. Using forecasting accuracy as the measure, the most likely path of Domestic electricity is that it follows the Harvey model forecasts. This means that the Domestic electricity consumption in Male' will grow at an exponential rate in the next 10 years. However, as the ARIMA models were ranked the best for forecasting Non-Domestic and Total consumption, it is expected that the electricity consumption in Male' for the Non-Domestic and Total consumption will increase at a more moderate rate in the future.

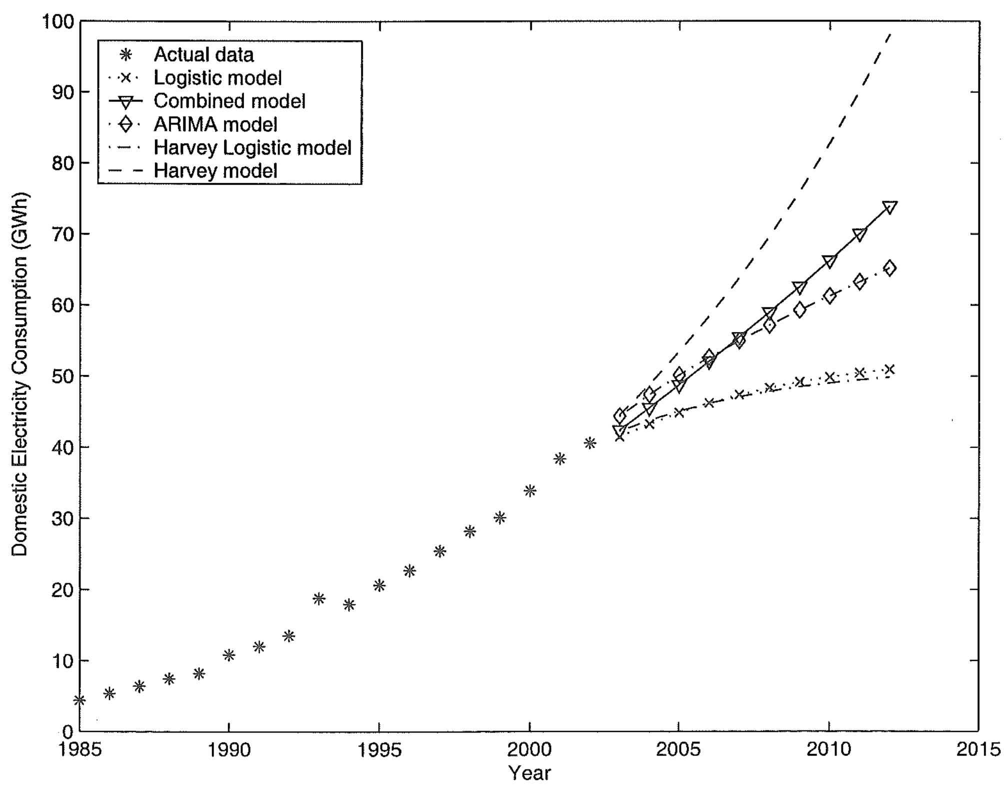

Figure 7.26 Comparison of Domestic forecasts for the Maldives

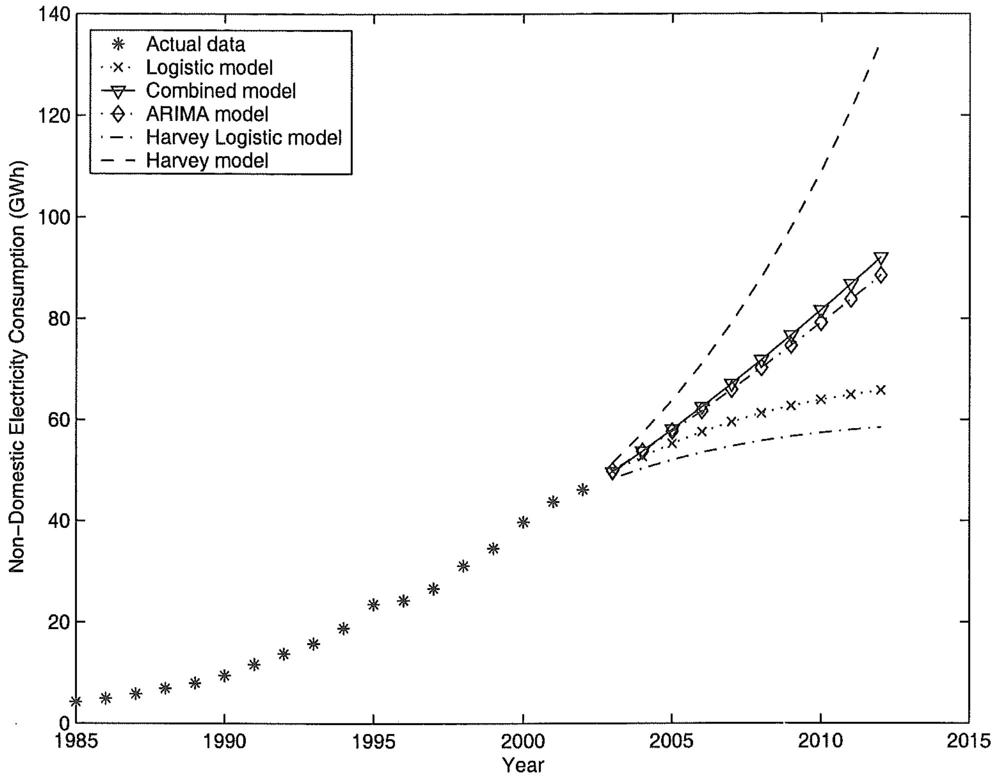

Figure 7.27 Comparison of Non-Domestic forecasts for the Maldives

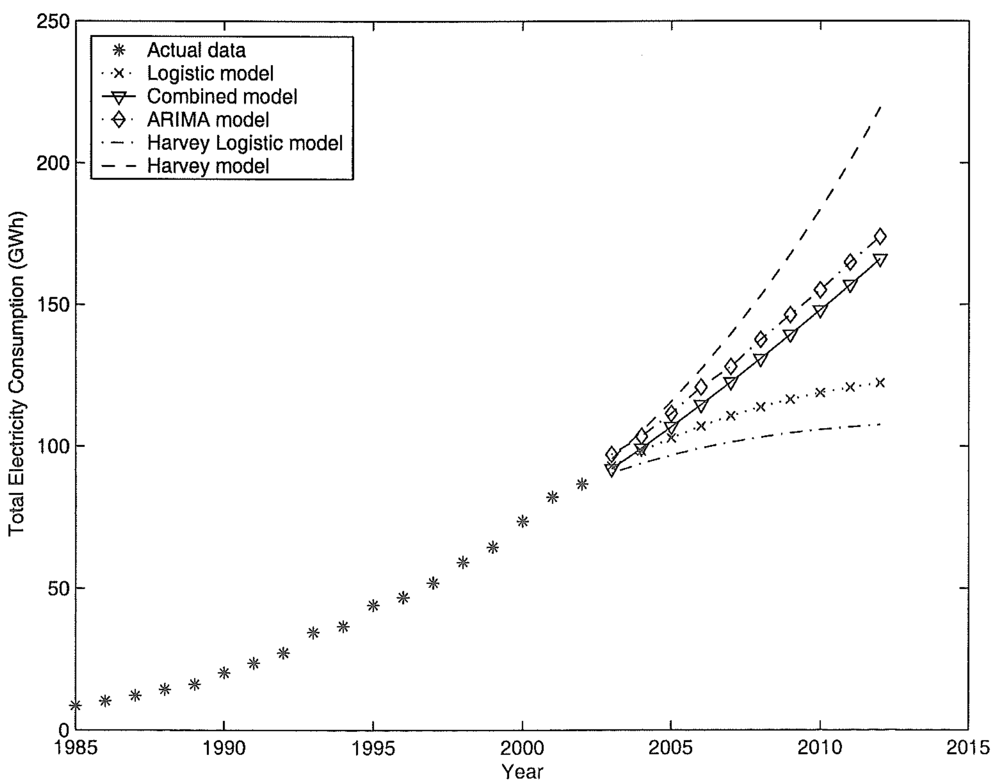

Figure 7.28 Comparison of Total electricity consumption forecasts for the Maldives

It should be noted that there are no official electricity consumption forecasts published in the Maldives.

7.10 SUMMARY

This chapter has summarised a brief history of electricity development in the capital island Male' of the Maldives. Five of the proposed forecasting models for electricity consumption are applied to Male'. They are the Logistic model, Combined model, Harvey Logistic model, Harvey model and ARIMA model. The VAL model was not found to be applicable to the Maldives at this stage.

The models were compared using their ability of model fit and forecasting accuracy in the short and medium term. The best model fit was given by the Harvey model for the Domestic sector, the Harvey and Harvey Logistic for the Non-Domestic sector and the ARIMA model for the Total consumption. The best overall forecasts were given by the Harvey model for the Domestic sector and the ARIMA models for the Non-Domestic sector and Total consumption. In all instances the worst forecasts were given by the Harvey Logistic and Logistic models. In general, the best models to forecast electricity consumption in Male' are the ARIMA, Harvey and Combined models. Finally, the forecasts given by the developed models have also been presented.

Chapter 8

FORECASTING ELECTRICITY CONSUMPTION IN THE UNITED STATES OF AMERICA

8.1 INTRODUCTION

The United States of America (USA) consumes the highest amount of electricity in the World. In 2002, the annual electricity consumption in the USA totalled to 3660 TWh, accounting to just over 25% of the total electricity consumed in the World [EIA, 2003]. In 2000, residential consumers paid an average of US$24.06 per million Btu for electricity as compared to an average of only US$7.49 for natural gas and US$12.58 for motor gasoline [EIA_3, 2004]. These figures clearly reflect that electricity is a great asset as a form of energy in costs to the end user. In 2000, 52% of electricity in the United States was produced by coal, 20% by nuclear, 19% by natural gas, petroleum, and other gases, 7% by hydroelectric power and 2% by non-hydroelectric renewable energy [EIA_3, 2004].

In this chapter, the proposed electricity forecasting models are applied and developed for the United States. This chapter aims to give a brief historical overview of the electricity development in the United States and apply the proposed models to the electricity consumption data. The developed models are also compared for forecasting accuracy over a nine year period. This chapter will be concluded by presenting the forecasts of the developed models and comparing them with some available forecasts for the United States.

8.2 OVERVIEW OF ELECTRICITY DEVELOPMENT

Electric power in the United States initially developed slowly. In 1880, Thomas Edison proved that a workable electric light could be made using primitive cotton-thread filament. This accelerated the growth of electricity development. In September 1882, Thomas Edison opened the first American power plant in New York [EIA_3, 2004]. Soon the number of light bulbs fed by the New York's Pearl Street station increased from 1300 in a month to 11,000 in a year [EIA_3, 2004].

Although Edison fathered the electric utility industry, his stubborn faith in direct current (DC) betrayed him [EIA_3, 2004]. Meanwhile, George Westinghouse and Nikola Tesla developed an alternating-current (AC) system that enabled long-distance transmission of high voltage current and step downs to lower voltages at the point of use. Between 1890 and 1910, mining, textiles, steel, and printing industries were rapidly electrified [EIA_3, 2004]. However, the penetration of the residential sector was slowed by the gas companies. Although the gas companies had a large proportion of the lighting market, by 1900 there were 25 million incandescent lamps in use and homeowners were introduced to electric stoves, sewing machines, curling irons and vacuum cleaners. By 1903, a 5 MW steam-driven turbine generator was commissioned by the utility executive Samuel Insull [EIA_3, 2004]. This was the first of its type and the largest of any generator then built. It launched a revolution in generating hardware.

Until President Franklin Roosevelt signed into law the Rural Electrification Administration (REA) in 1935, electric service to rural Americans was delayed due to the high costs and Great Depression that dried up most of the investment capital [EIA_3, 2004]. The REA allowed low interest loans that helped to set up electricity cooperatives. Although there was some interruption by World War II, by 1967 more than 67 percent of American farms were using electricity from central power plants [EIA_3, 2004]. From 1949 to 2002, the population of the United States expanded 89 percent, while the amount of electricity consumed increased 1315 percent [EIA_3, 2004]. In 2000, the highest consumption in electricity was by the residential sector, followed closely by the industrial and then the commercial sector.

In 1949 hydropower accounted for almost a third of the generation. The use of natural gas and petroleum grew steadily in the late 1960s. A new source of power, nuclear electricity began flowing in 1957. Following the accident at Three Miles Island, the increase in the flow of nuclear electricity decreased in 1979 and 1980 [EIA_3, 2004]. In 2000, nuclear power accounted for 20 percent of total electricity generated in the United States [EIA_3, 2004].

The electric power sector is now moving away from its traditional, highly regulated organisations, known for decades as electric utilities, towards an environment marked by lighter regulation and greater competition from and among non-utility power producers [EIA_3, 2004]. The non-utility power producers include independent power producers and non-utility co-generators. In 2000, the non-utility power producers were supplying 26 percent of total net summer capability, as compared to 20 percent in 1999.

8.3 HISTORICAL ELECTRICITY CONSUMPTION

The electricity consumption data in the United States has been divided into the Domestic and the Non-Domestic sectors, to be consistent with the case for New Zealand and the Maldives. The Domestic sector consists of residential customers only while the Non-Domestic sector contains the commercial, industrial and other customers. These data are obtained from the Energy Information Administration [EIA, 2003]. Details of these data are given in Appendix A.

The annual electricity consumption in the United States from 1949 to 2002 for the Domestic and the Non-Domestic sectors and the Total consumption are shown in Figure 8.1. While there is a relatively linear increase in growth in the Domestic sector, the growth in the Non-Domestic sector has changed more frequently over the years. The Total consumption, which is an admixture of the Domestic and the Non-Domestic sectors, reflects the variations in the Non-Domestic sector due to the steady increase in the Domestic sector.

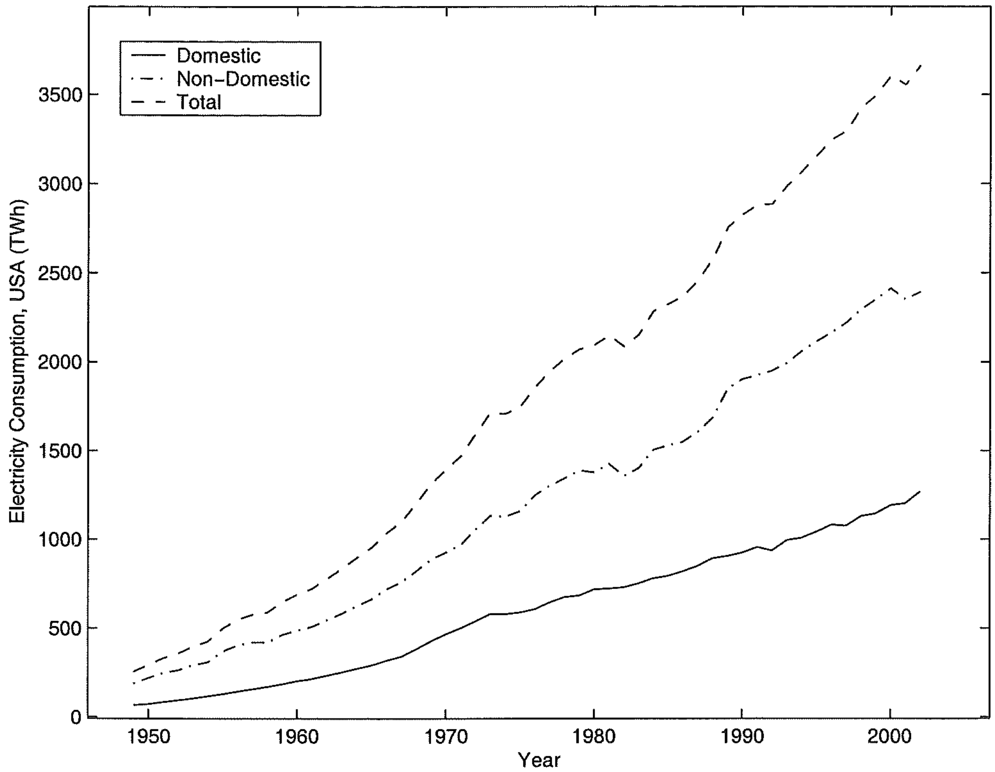

Figure 8.1 Annual electricity consumption in the United States 1949-2002

8.4 THE LOGISTIC MODEL

As applied previously, the asymptotes *F* of the Logistic model are obtained by the developed Fibonacci search technique [Boas, 1963] for the Domestic, the Non-Domestic and the Total consumptions of the United States and are shown in Table 8.1.

Table 8.1 Saturation levels for the USA by Fibonacci search technique

Sector	Data Year	*F* (TWh)
Domestic	1949-2002	1360
Non-Domestic	1949-2002	2954
Total	1949-2002	4354

The saturation levels of the Domestic and the Non-Domestic sectors add to 4314 TWh as compared to the saturation level of 4354 TWh in the Total consumption. This is within 1% of the saturation level of the Total consumption. This indicates that the

Domestic and Non-Domestic sectors are mature in terms of their growth in electricity consumption. The fitted Logistic models along with the actual data are shown in Figure 8.2 for the Domestic, the Non-Domestic and the Total consumption. The corresponding mean absolute percentage errors (MAPE) are 5.9, 5.0 and 5.2 for the Domestic, the Non-Domestic and the Total consumption respectively.

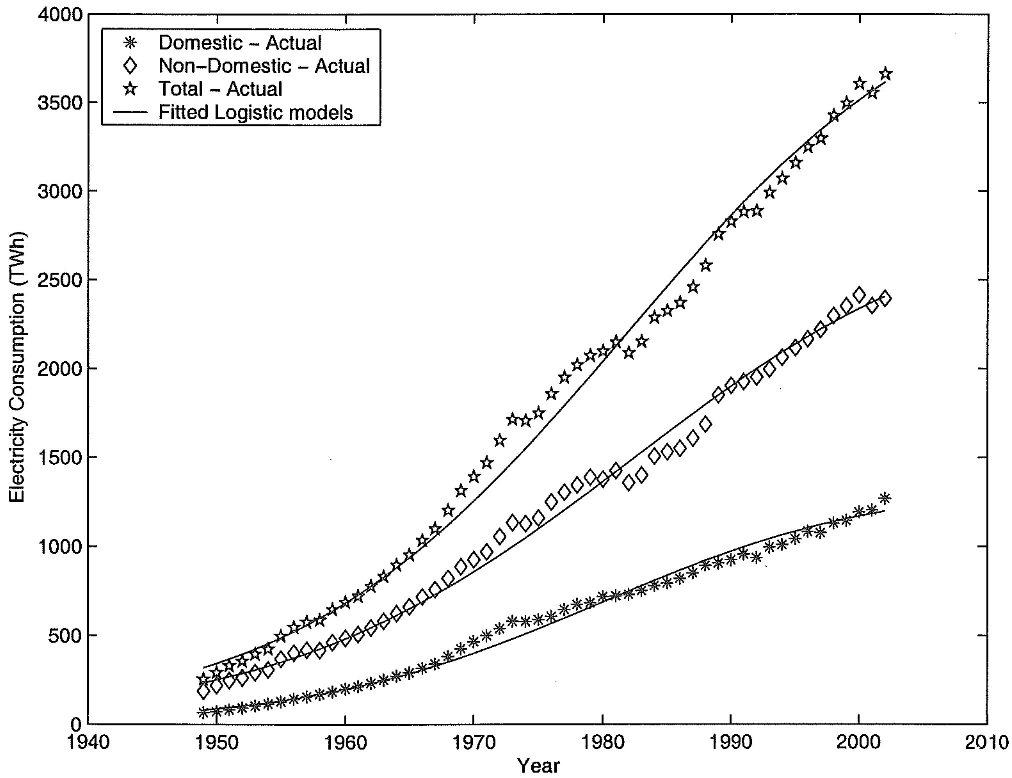

Figure 8.2 Fitted Logistic models for the United States

The Logistic model has produced quite good fits of the earlier and later data in all cases. While there are some deviations from the actual values from the early 1970s to the late 1980s, overall all the models have produced acceptable fits of the historical data with low MAPE values. In the worst fit of the Domestic sector, a MAPE value of 5.9% was obtained.

8.5 THE COMBINED MODEL

The variables used in developing the Combined model for the United States are the gross domestic product (GDP), population and price of electricity. These data are obtained from the Energy Information Administration [EIA, 2003] and are listed in Appendix A. The strength of the relationships between the selected variables and electricity consumption are shown by their respective correlation coefficients. The correlation coefficients between the selected GDP, population and price of electricity, and electricity consumption are given in Table 8.2. The GDP (in billions of US $) and price (in US cents/ kWh) are in real terms.

Table 8.2 Correlation coefficients between the selected variables and the electricity consumption

	Domestic	Non-Domestic	Total	GDP	Population	Price
Domestic	1			0.984	0.994	-0.036
Non-Domestic		1		0.990	0.995	-0.069
Total			1	0.990	0.996	-0.058
GDP				1	0.995	-0.103
Population					1	-0.055
Price						1

The correlation coefficients of GDP and population are very high for all cases of electricity consumption. However, the correlation between price of electricity and electricity consumption are very low such that the price of electricity is discarded from being used in the multiple linear regression model. Thus, the variables used in constructing the Combined model are the GDP and population of the United States.

The proposed Combined model for the United States is

$$Y = a + b_1 X_1 + b_2 X_2 \qquad (8.1)$$

where,

Y is the electricity consumption in TWh,

X_1 is GDP (in billions of US dollars),

X_2 is population, and

a, b_1 and b_2 are constants.

The statistical ability of the chosen variables to forecast electricity consumption should be tested before finalising the model. The results of the validity tests that consist of adjusted coefficient of determination r^2, F-test and t-test [Makridakis *et al.*, 1998] are given in Table 8.3.

Table 8.3 Validity test results for the USA

	adjusted	F- test		t -test		
	r^2	99% value	F	99% value	t_1	t_2
Domestic	0.980	5.16	2059	2.42	-28.31	93.1
Non-Domestic	0.981	5.16	2146	2.42	-1.71	68.0
Total	0.984	5.16	2593	2.42	-12.1	84.9

The adjusted coefficient of determination are high in all cases implying that even in the worst case of the Domestic consumption, 98% of the variance in electricity consumption is explained by the combination of GDP and population for the United States. Therefore, each of those consumption models coupled with a good forecast of GDP and population should produce a good forecast of electricity consumption. The 99% critical values of F for each of the sectors are much lower than the actual F obtained indicating that a multiple linear regression model using these variables is significant. The absolute value of the t- test results t_1 and t_2 for the coefficients of X_1 and X_2 are higher than the 99% critical value of t in all cases except for t_1 of the Non-Domestic sector. However, the value of 1.71 is still higher than the 95% critical value of 1.68. Therefore, it is acceptable at the 95% probability level. This means that each of those coefficients b_1 and b_2 are significantly different from zero.

Figure 8.3 shows the residuals produced by the Combined model against the fitted values and the variables used in the model. There is no apparent pattern in any of the plots indicating that the residuals produced by each of the models are independent. These plots along with the statistical results and the correlation coefficients suggest that a multiple linear regression model using GDP and population should produce acceptable forecasts for the United States. The resulting fitted models for the Domestic and the Non-Domestic sectors and the Total electricity consumption are shown in Figure 8.4.

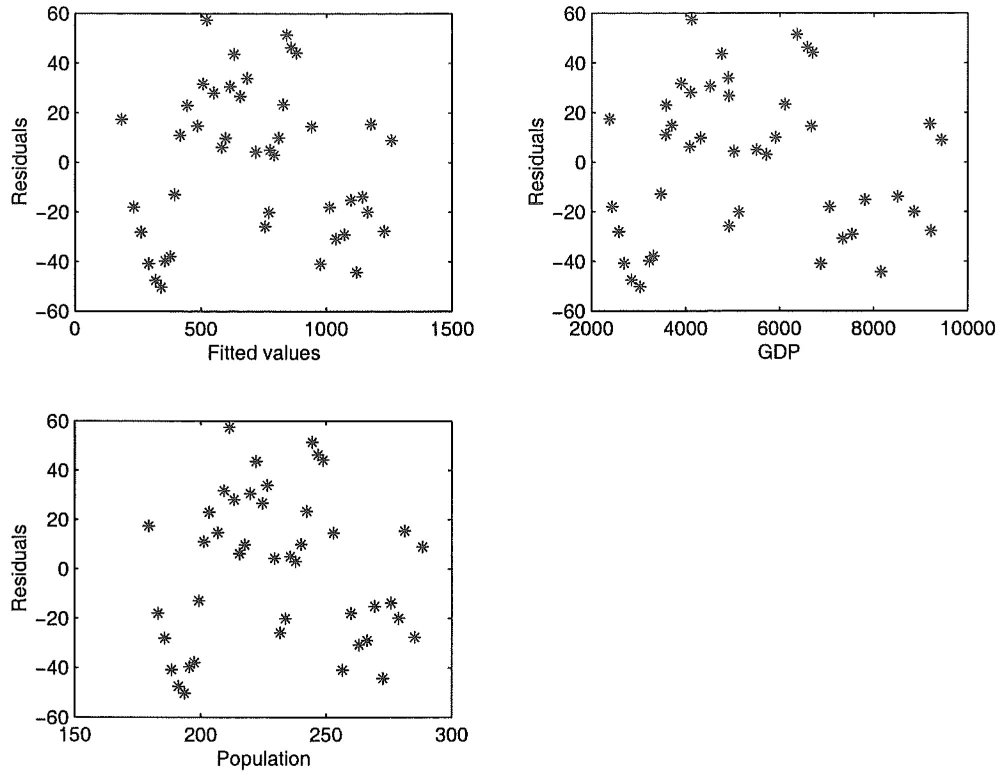

Figure 8.3 Residuals against the fitted variables of the Combined model

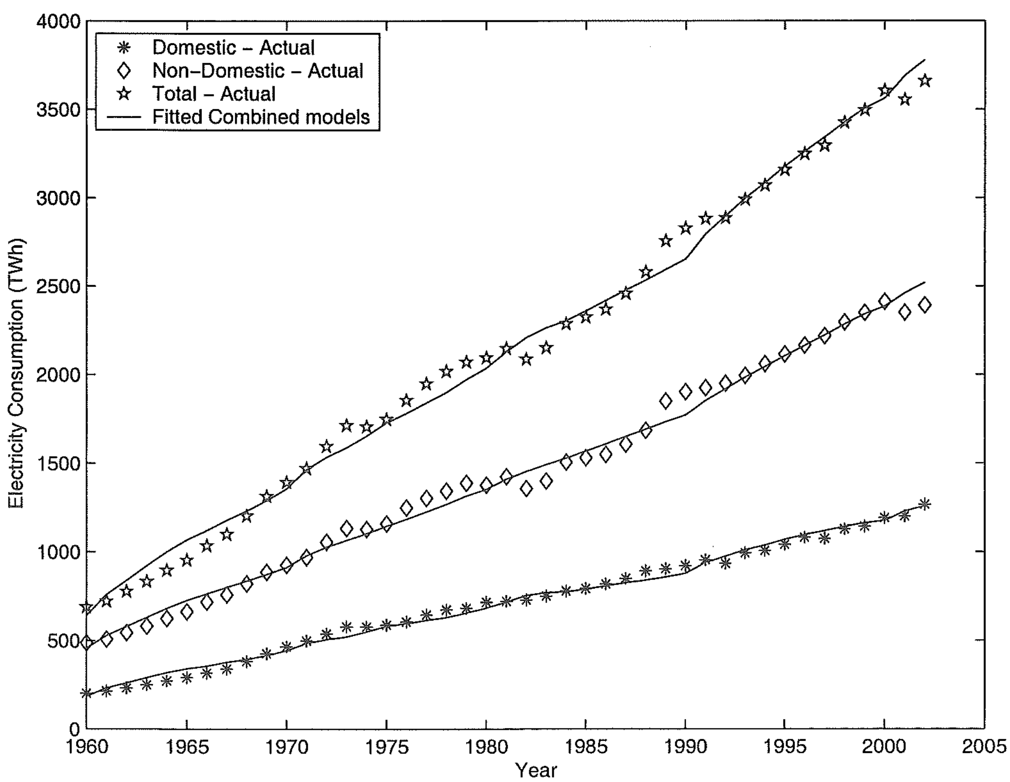

Figure 8.4 Fitted Combined models for the United States

The Combined model has produced very good fits of the historical data with low MAPE values of 5.1 for Domestic, 3.7 for Non-Domestic and 3.9 for Total electricity consumption of the United States. Thus, even in the worst case of the Domestic sector, the average error is 5.1%. In making electricity consumption forecasts using the Combined models the variables GDP and population need to be independently forecasted. These variables are forecasted using the Autoregressive Integrated Moving Average (ARIMA) techniques.

8.6 ARIMA MODELS

The steps involved in ARIMA modelling are identification, estimation, testing and forecasting [Makridakis *et al.*, 1998]. These steps are applied separately to each of the Domestic, the Non-Domestic and the Total electricity consumption of the United States.

8.6.1 Domestic ARIMA Model

Figure 8.5 shows the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the original Domestic electricity consumption of the United States. The $\pm 1.96/\sqrt{n}$ bounds for stationarity are shown by the dotted lines. A significant number of autocorrelations are outside the limits indicating non-stationarity. The first partial autocorrelation coefficient is very dominant and close to 1, also indicating non-stationarity. Figure 8.6 shows the ACF and PACF plots of the differenced data. All correlation coefficients except the second of each ACF and PACF plots are within the bounds of stationarity. As the correlations are within the required bounds more than 95% of the time, it can be concluded that the series is now stationary. Therefore the process of identification and estimation can now be carried out. The identification and estimation processes are assisted by the use of the software ITSM2000 [Brockwell and Davis, 2002]. The best model for the Domestic sector is selected based on the lowest AICC value [Brockwell and Davis, 2002]. The best model for the Domestic sector using this criterion is ARIMA(3,1,3).

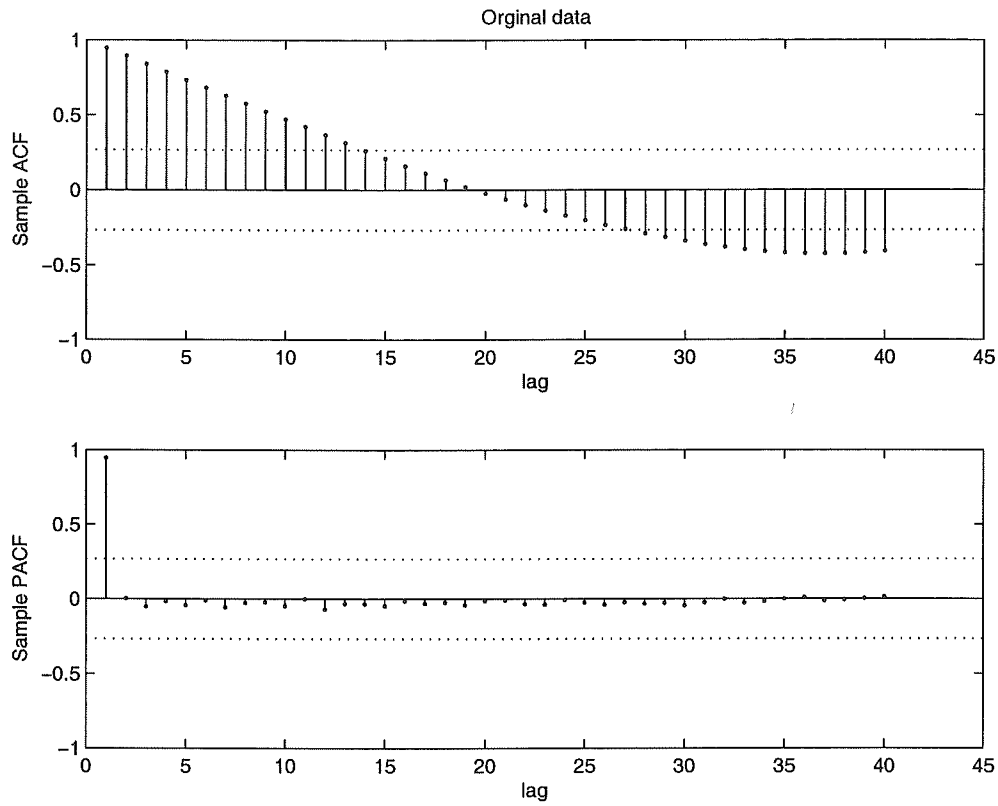

Figure 8.5 ACF and PACF plots of the Domestic sector for the United States

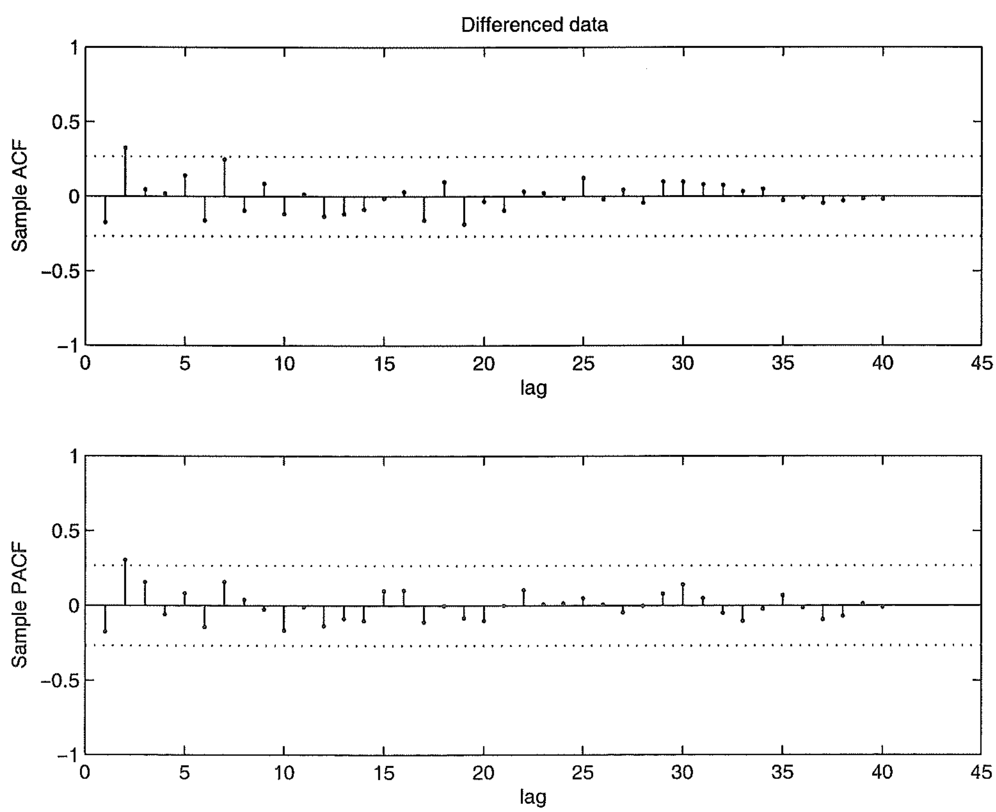

Figure 8.6 ACF and PACF plots of the differenced Domestic data

The maximum likelihood estimate for the ARIMA(3,1,3) model is

$$Y_t' = -0.950Y_{t-1} + 0.604Y_{t-2} + 0.835Y_{t-3} + e_t + 1.269e_{t-1} - 0.370e_{t-2} - 0.694e_{t-3} \qquad (8.2)$$

where e_t is approximated by a zero mean white noise (WN) sequence, i.e. e_t ~ WN(0, 151). Since the data is differenced and mean corrected before estimation, $Y_t' = Y_t - Y_{t-1} - 22.67$ and thus

$$Y_t = 22.67 + 0.005Y_{t-1} + 0.604Y_{t-2} + 0.835Y_{t-3} + e_t + 1.269e_{t-1} - 0.370e_{t-2} - 0.694e_{t-3} \quad (8.3)$$

The fit to the historical data given by the ARIMA(3,1,3) model for the Domestic sector is shown in Figure 8.7.

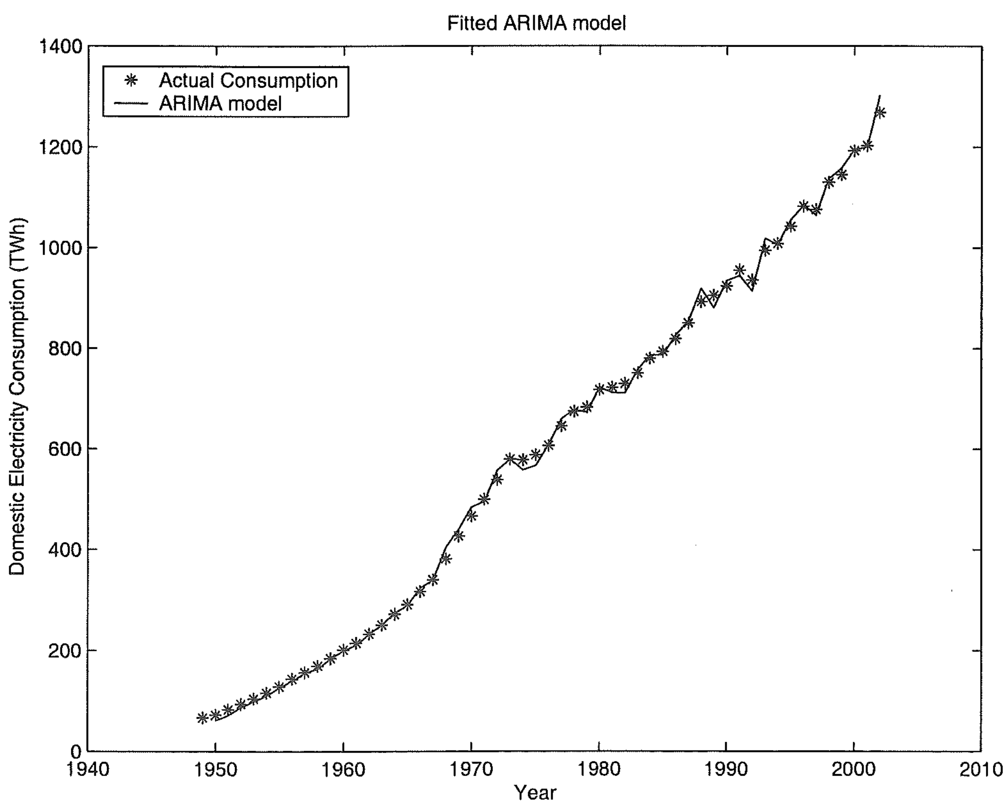

Figure 8.7 Fitted ARIMA(3,1,3) model for the Domestic sector (MAPE = 2.28)

The ARIMA(3,1,3) model has produced very good estimates of the historical Domestic sector. However, the model could only be accepted provided it could satisfy the required statistical tests. Figure 8.8 shows the ACF and PACF of the residuals produced by this model. It can be seen that the residuals are well within the bounds for stationarity. Thus, the residuals produced by the ARIMA(3,1,3) models are white noise. In addition, the Ljung-Box Q statistic (for lags h = 20) gives a Q value of 14.05. This is much lower than the corresponding critical chi-square of 31.41 at 95% probability level. This test further suggests that the residuals produced by the ARIMA(3,1,3) model are not significant. Having passed the diagnostic tests, the ARIMA(3,1,3) model is proposed for the Domestic electricity consumption forecasting in the United States.

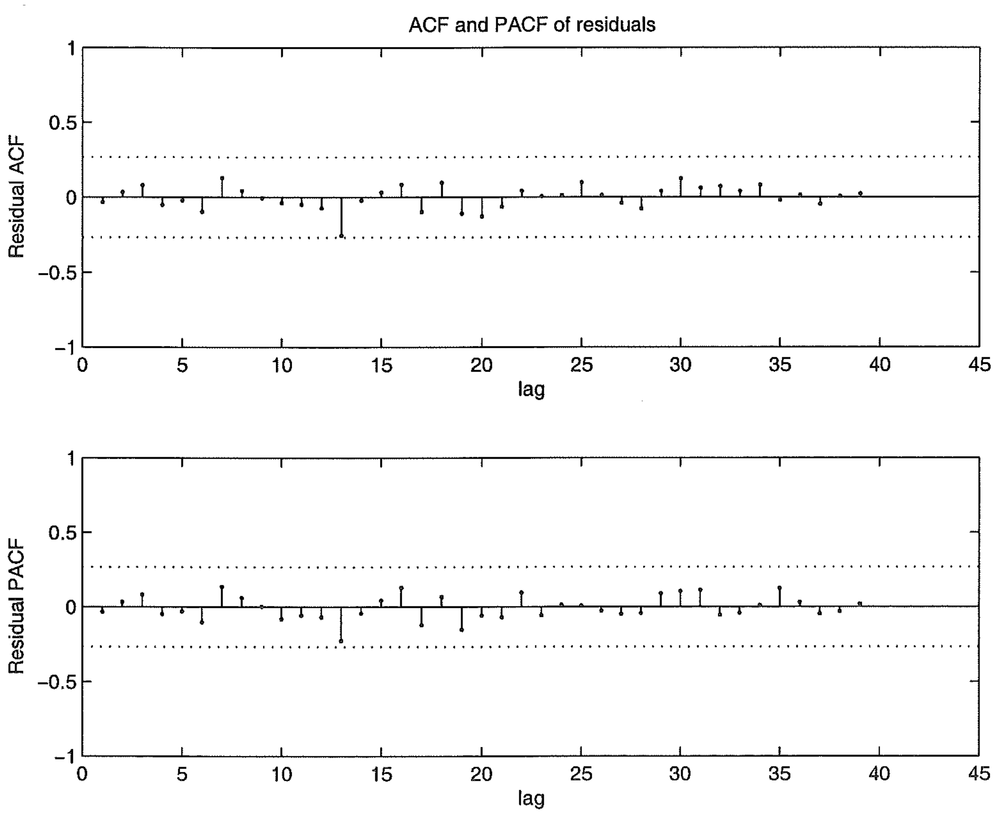

Figure 8.8 ACF and PACF of the residuals produced for the Domestic sector

8.6.2 Non-Domestic ARIMA Model

The ACF and PACF plots of the Non-Domestic sector are very similar to that of the Domestic sector shown in Figure 8.5 indicating non-stationarity. Therefore, the Non-

Domestic data is differenced. The ACF and PACF of the differenced data are shown in Figure 8.9.

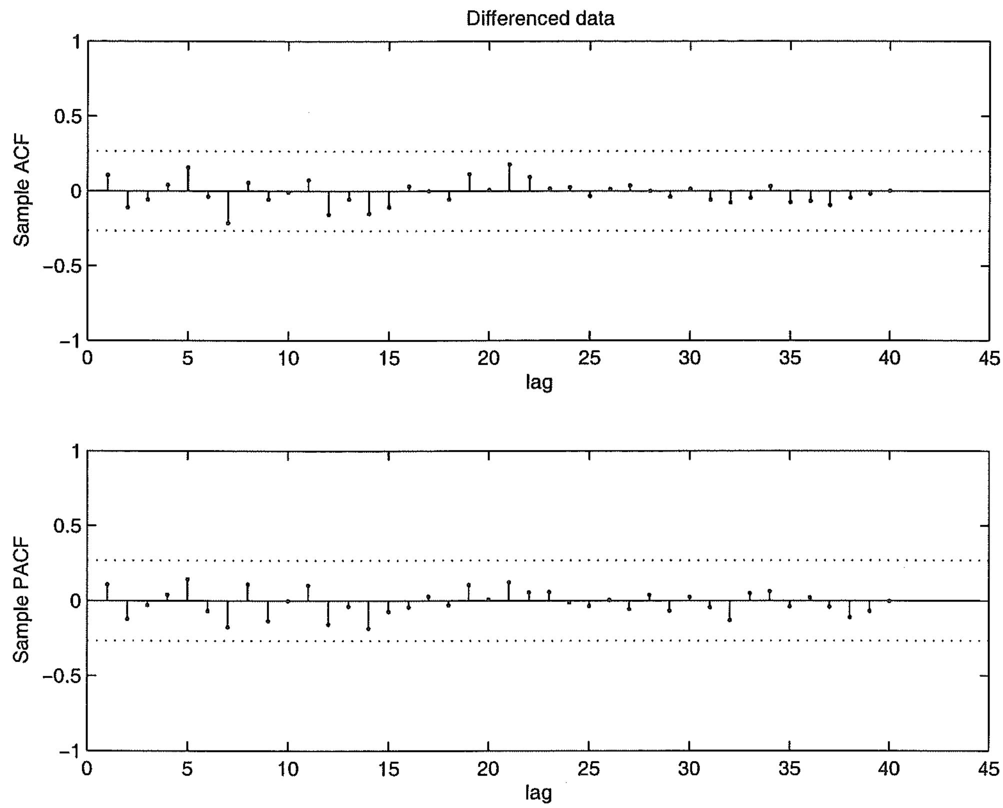

Figure 8.9 ACF and PACF plots of the differenced Non-Domestic data

The ACF and PACF coefficients of the differenced data are all well within the limits of stationarity. The best model selected for the Non-Domestic sector based on the lowest AICC value is ARIMA(0,1,0). The maximum likelihood estimate of the model is

$$Y_t' = e_t \tag{8.4}$$

where e_t is approximated by a zero mean white noise (WN) sequence, i.e. $e_t \sim$ WN(0, 1232).

Since the data is differenced and mean corrected before estimation, $Y_t' = Y_t - Y_{t-1} - 41.59$ and thus

$$Y_t = 41.59 + Y_{t-1} + e_t \tag{8.5}$$

The resulting ARIMA(0,1,0) model fit for the Non-Domestic sector is shown in Figure 8.10. It can be seen that the ARIMA(0,1,0) model has produced very good fits of the historical data.

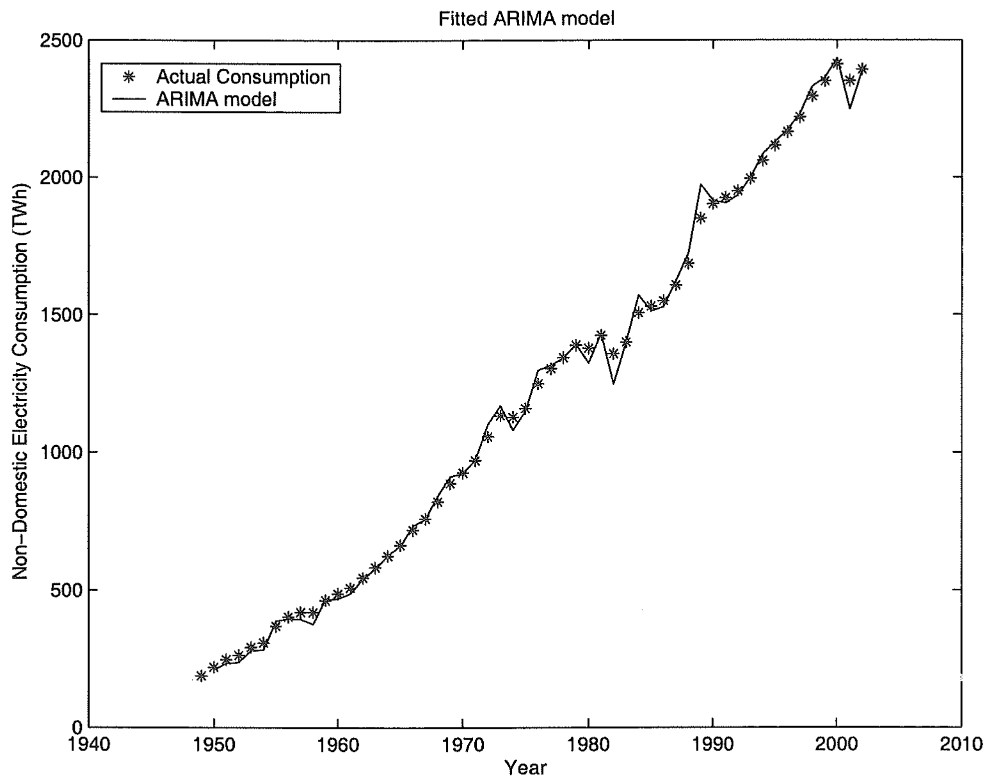

Figure 8.10 Fitted ARIMA(0,1,0) for the Non-Domestic sector (MAPE = 2.51)

The ACF and PACF of the residuals produced by this model fit are shown in Figure 8.11. All the residuals are well within the limits of stationarity, indicating that the residuals produced by the model are white noise. The Ljung-Box Q statistic [Brockwell and Davis, 2002] for lags h = 20 gives a Q value of 12.95. This is much lower than the critical chi-square of 31.41 at the 95% probability level suggesting once again that the residuals produced by the ARIMA(0,1,0) model for the Non-Domestic sector are not significant. Thus the ARIMA(0,1,0) model is proposed for the Non-Domestic electricity consumption in the United States.

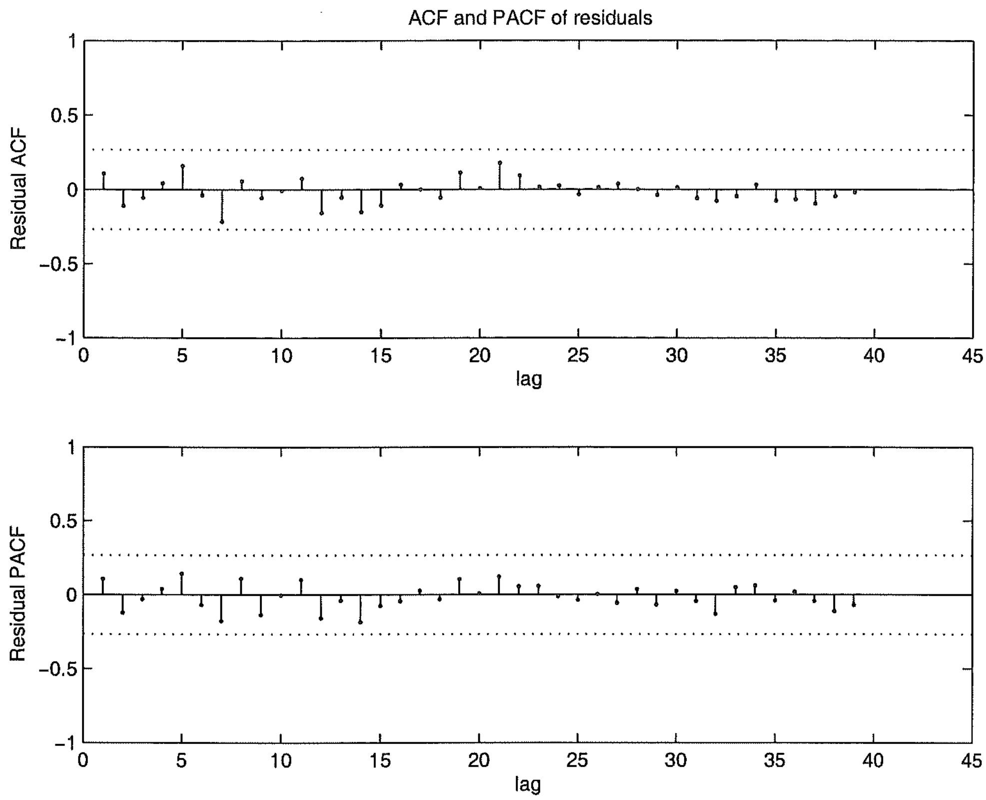

Figure 8.11 ACF and PACF of the residuals produced for the Non-Domestic sector

8.6.3 ARIMA Model for the Total Electricity Consumption

The ACF and PACF plots of the original Total consumption data are again very similar to the Domestic and the Non-Domestic sectors suggesting non-stationarity. Therefore, the data is differenced at lag 1. The ACF and PACF plots of the differenced data are shown in Figure 8.12. The ACF and PACF plots are well within the $\pm 1.96/\sqrt{n}$ bounds indicating stationarity. Thus, the best model is identified using the AICC criteria. The best model, with the lowest AICC, is ARIMA(0,1,0). The estimated ARIMA(0,1,0) model is

$$Y_t' = e_t \tag{8.6}$$

where e_t is approximated by a zero mean white noise (WN) sequence, i.e. e_t ~ WN(0, 1862). After adjusting for the differencing and mean correction, the final model becomes

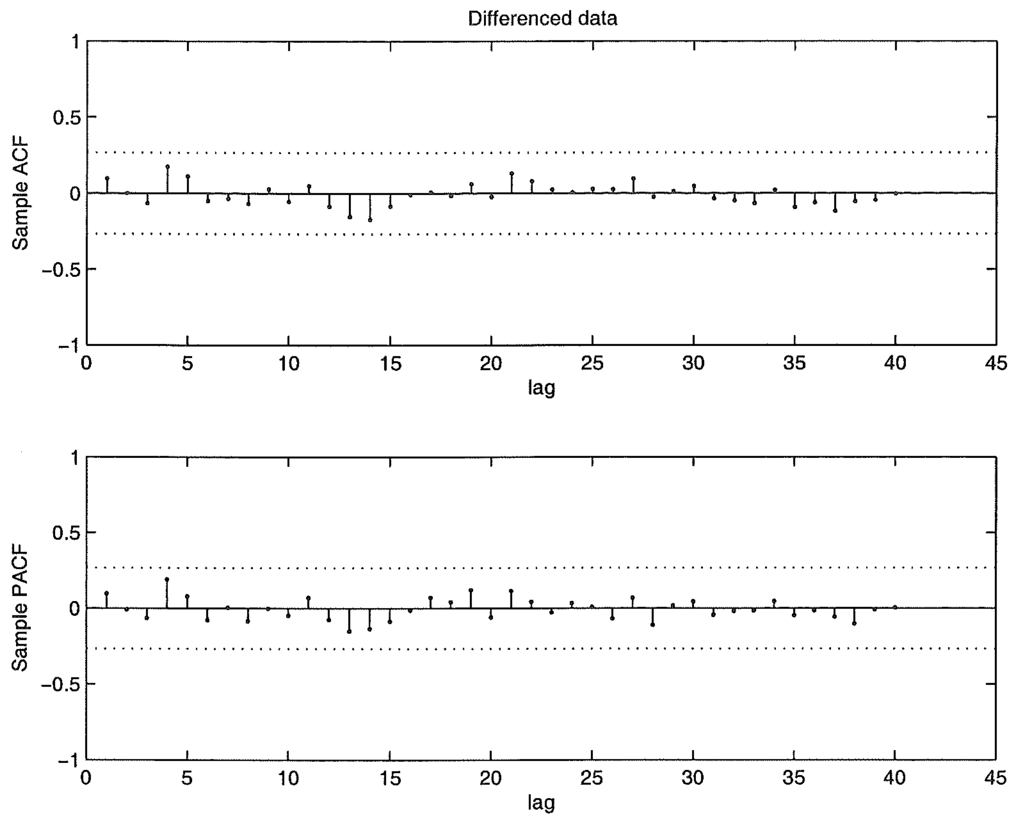

Figure 8.12 ACF and PACF of the differenced Total consumption data

$$Y_t = 64.25 + Y_{t-1} + e_t \tag{8.7}$$

The estimate of the Total electricity consumption given by the ARIMA(0,1,0) model is shown in Figure 8.13. The ARIMA(0,1,0) model has produced very good fits of the historical data with similar MAPE values as the Domestic and the Non-Domestic sectors.

The ACF and PACF of the residuals produced by this model are shown in Figure 8.14. All the residuals are again within the limits of stationarity, indicating that the residuals are white noise. The Ljung-Box statistic gives a Q value of 9.67. This is much lower than the critical chi-square of 31.41 at the 95% probability level suggesting once again that the residuals produced by the ARIMA(0,1,0) model for the Total electricity consumption are not significant. Thus, the selected model for the Total electricity consumption forecasting in the United States is ARIMA(0,1,0).

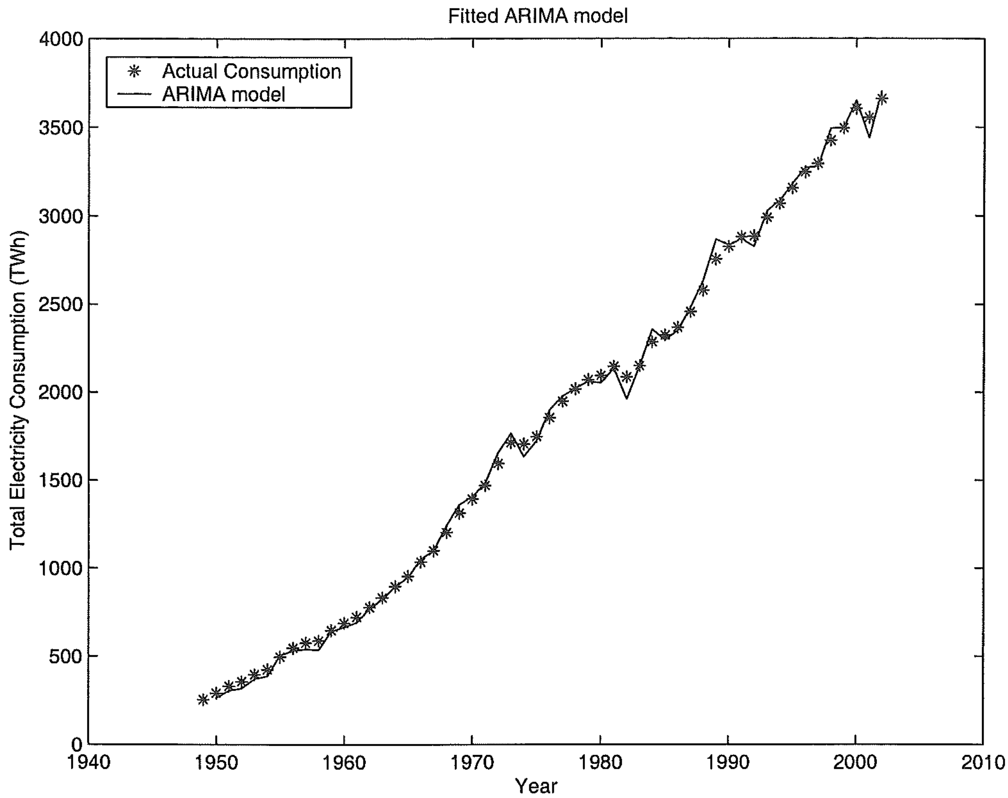

Figure 8.13 ARIMA(0,1,0) estimate of the Total electricity consumption (MAPE = 2.56)

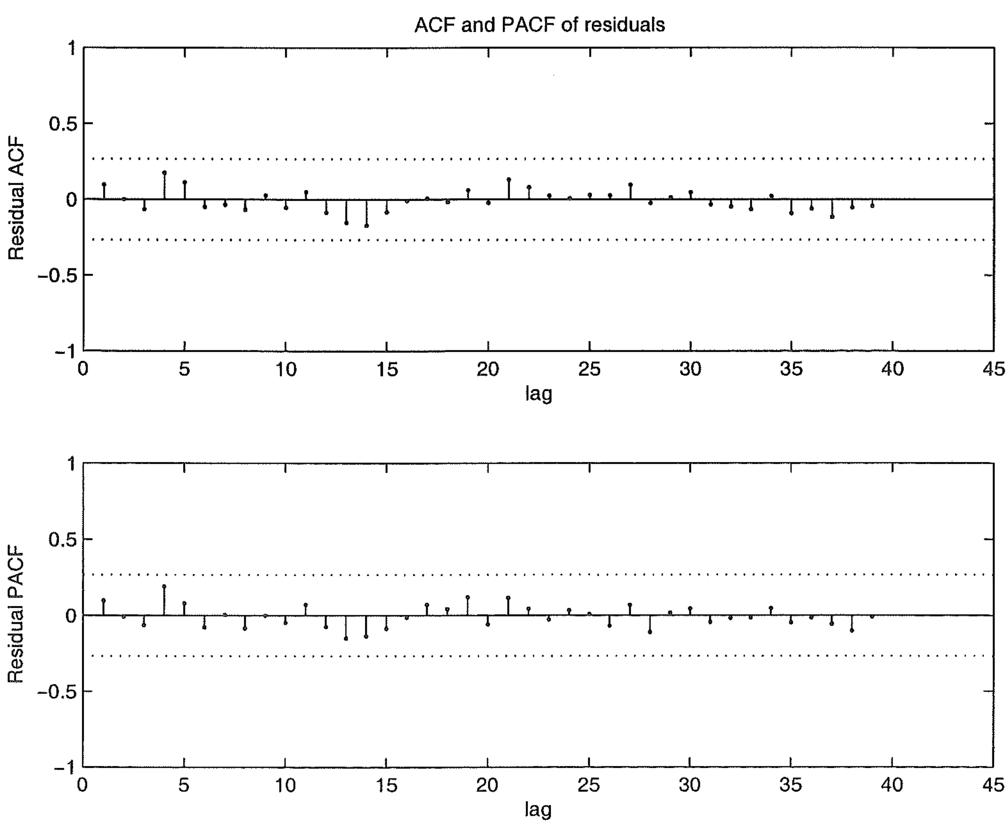

Figure 8.14 ACF and PACF of the residuals for the Total electricity consumption

8.7 HARVEY LOGISTIC AND HARVEY MODELS

The Harvey Logistic and Harvey models are applied to the Domestic, the Non-Domestic and the Total electricity consumption data of the United States. The resulting Harvey Logistic models are

Domestic:	$\ln y_t = 2\ln Y_{t-1} + 170.1 - 0.091t$	(8.8)
Non-Domestic:	$\ln y_t = 2\ln Y_{t-1} + 131.5 - 0.072t$	(8.9)
Total:	$\ln y_t = 2\ln Y_{t-1} + 151.0 - 0.082t$	(8.10)

And the resulting Harvey models are

Domestic:	$\ln y_t = 0.201\ln Y_{t-1} - 6.629 + 0.0042t$	(8.11)
Non-Domestic:	$\ln y_t = 0.119\ln Y_{t-1} - 24.64 + 0.0139t$	(8.12)
Total:	$\ln y_t = 0.262\ln Y_{t-1} - 0.262 + 0.0012t$	(8.13)

In both cases, t is the time in years from 1949.

The two models have produced very different coefficients indicating that the Harvey Logistic models are significantly different from the Harvey models. The fitted Harvey Logistic and Harvey models for the Domestic, the Non-Domestic and the Total consumption are shown in Figure 8.15 and 8.16 respectively.

The MAPE values of the fitted Harvey Logistic models are 2.20, 2.41 and 2.11, while those for the Harvey models are 1.98, 2.18 and 1.83 for the Domestic, the Non-Domestic and the Total electricity consumption respectively. The Harvey Logistic and Harvey models have produced very good fits of the historical data. The Harvey models have produced even better fits than those for the Harvey Logistic models. The DW values for the Harvey Logistic models are 2, 1.8 and 1.8 while those for the Harvey models are 2.3, 1.8 and 1.9 for the Domestic, the Non-Domestic and the Total consumption respectively. All these values are close to the desired value of 2 suggesting that the residuals given by the developed models are white noise.

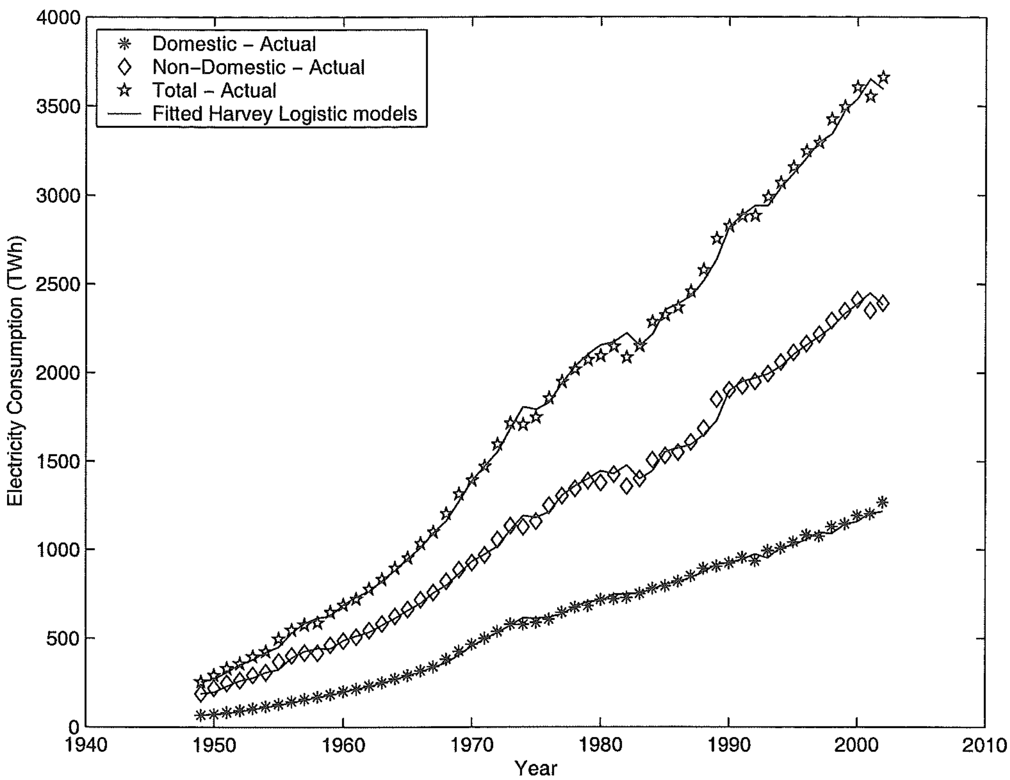

Figure 8.15 Fitted Harvey Logistic models for the United States

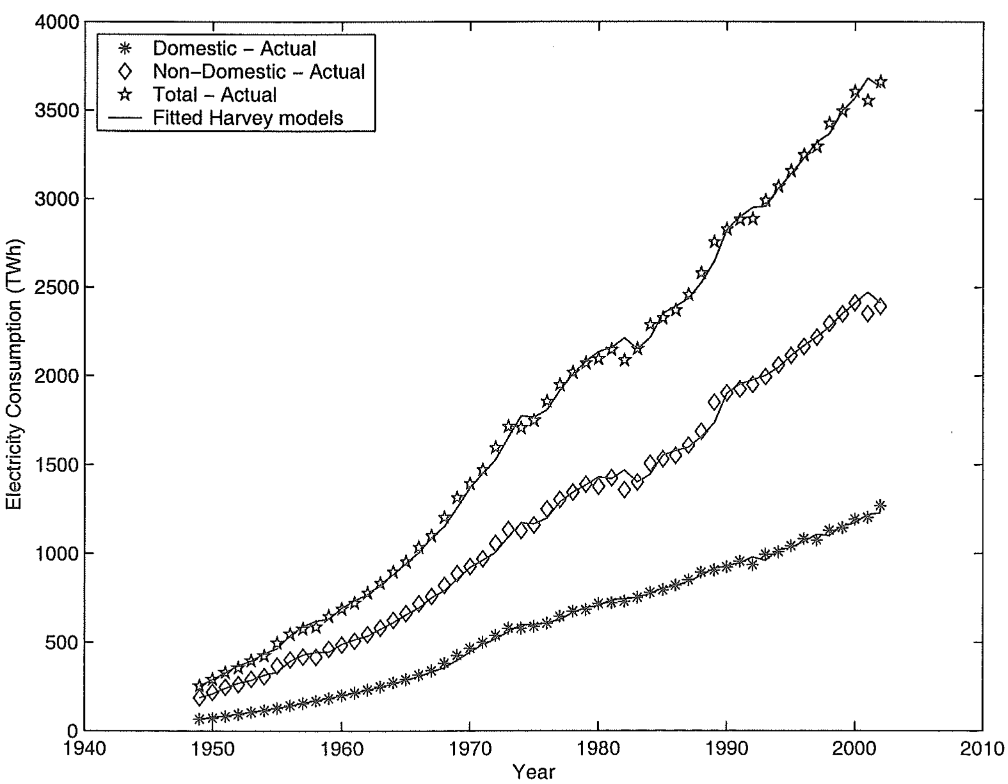

Figure 8.16 Fitted Harvey models for the United States

8.8 THE VAL MODEL

8.8.1 Fibonacci Search Technique

The first step in the VAL model is to calculate the saturation level for a selected period using the Fibonacci search technique. The Fibonacci search technique is applied to the Domestic, the Non-Domestic and the Total electricity consumption data of the United States from 1949-1985, 1949-1986, ….,1949-2002 and the saturation levels are obtained for 1985, 1986, …., 2002 respectively. Figure 8.17 shows the saturation levels obtained.

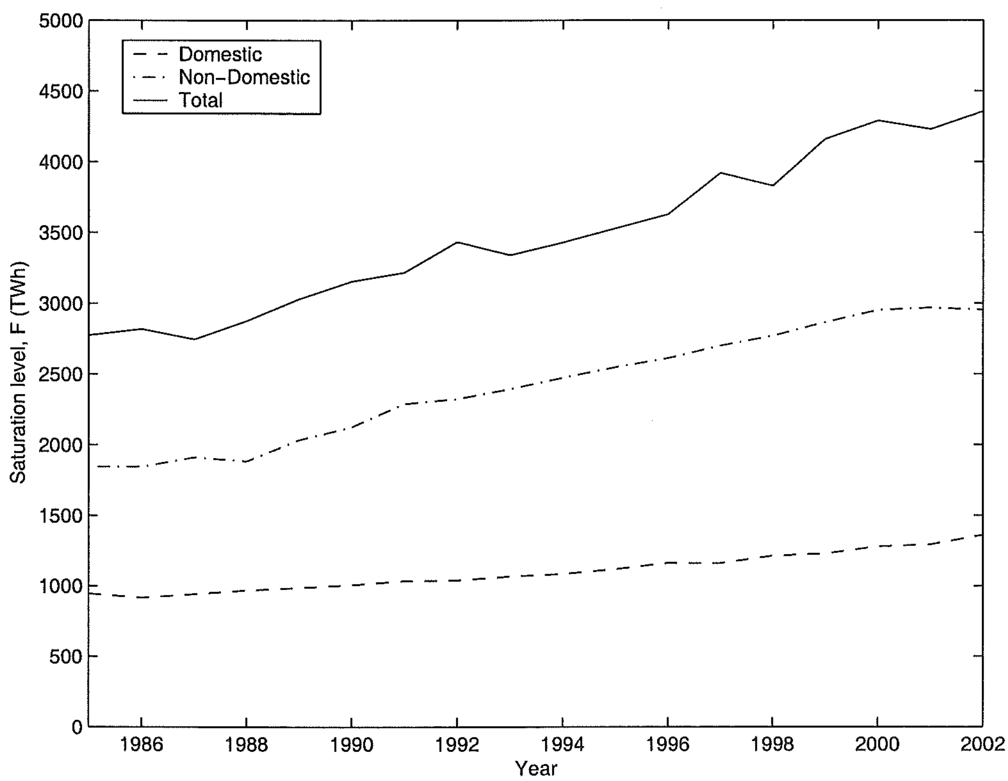

Figure 8.17 Saturation levels obtained by the Fibonacci search technique from 1984-2002

The saturation levels in all cases are gradually increasing. The saturation levels in the Domestic and the Non-Domestic sectors are uniformly increasing while the saturation levels for the Total consumptions shows some level of non-uniformity in the increasing trend.

8.8.2 Re-estimation of the Saturation Level

The correlation between the explaining variables and the saturation levels obtained by the Fibonacci search technique should be high enough for the variables to be used in re-estimation of the saturation level by a multiple linear regression technique. Table 8.4 shows the correlation between the explaining variables GDP, population and price of electricity, and the saturation levels of electricity consumption obtained by the Fibonacci search technique.

Table 8.4 Correlation between the explaining variables and the saturation levels

Saturation	Explaining variables		
	GDP	Population	Price
Domestic	0.994	0.996	-0.956
Non-Domestoc	0.962	0.971	-0.948
Total	0.984	0.995	-0.967

All the explaining variables are highly correlated with the saturation level of electricity. Although the price of electricity correlated poorly with the actual electricity consumption as shown previously in Table 8.2, it has given very high correlations with the saturation levels of electricity obtained by the Fibonacci search technique. Therefore, it was initially decided to re-estimate the saturation levels using all possible combinations of explaining variables and select the best VAL model at a later stage on the basis of how well the variables re-estimate the saturation levels obtained by the Fibonacci search technique and their forecasting accuracy. This approach was used in proposing the best VAL model for New Zealand (Chapter 6), and therefore the same method is followed here. The combinations of variables in the VAL models are

Model 1: GDP and Population

Model 2: GDP and Price

Model 3: Population and Price

Model 4: GDP, Population and Price

The saturation levels for the Domestic, the Non-Domestic and the Total electricity consumption of the United States are re-estimated using each of these models by the multiple linear regression technique. Table 8.5 summarises the test results of the Durbin-Watson (DW) statistic, coefficient of determination r^2 and F test [Makridakis *et al.*, 1998].

Table 8.5 Statistical test results for re-estimation of saturation levels

Model No.	Domestic			Non-Domestic			Total			99%
	DW	r^2	F	DW	r^2	F	DW	r^2	F	critical F
1	1.7	0.99	1160.5	1.1	0.99	505.9	2.0	0.98	332.3	6.1
2	1.2	0.99	633.5	1.4	0.93	102.0	0.9	0.99	333.4	6.1
3	1.2	0.99	744.0	1.6	0.94	120.2	1.1	0.99	884.3	6.1
4	1.7	0.99	733.9	1.6	0.94	74.8	1.1	0.98	559.7	5.2

In the Domestic sector, the best results are given by Model 1 with a DW value close to 2 and the highest r^2 and F values. In the Non-Domestic sector the best DW is given by Model 4, but gave the worst r^2 and F values. The best r^2 and F values are given by Model 1. In the Total consumption, Model 1 gave a perfect DW value of 2 and among the best r^2 and F values. The DW values for all other models are much lower than 2 as compared to Model 1. These analyses suggest that Model 1 which uses GDP and population gives the best re-estimate of the saturation levels. However, a final choice of these models will be selected after comparing the forecasting accuracy of the models as well.

8.8.3 Choice of VAL Model

The re-estimated saturation levels by each of the models need to be forecasted so that the forecasting accuracy over a selected period can be calculated. This requires forecasting the explaining variables. The ARIMA technique is used to forecast these explaining variables. Forecasting accuracies of the four models are calculated over a period of nine years from 1994 to 2002. While calculating the forecasting accuracy of the 9 year ahead forecast, all data after 1993 are discarded and not used in obtaining the models. Forecasts of the explaining variables are used to get future estimates of the saturation level for each of the forecasted periods from 1994 to 2002. The asymptotic value of each of the forecasted periods is used to obtain the forecasts. This is a variable asymptote method as opposed to the constant asymptotic level used by the original Logistic model, and hence the name Variable Asymptote Logistic (VAL) model. The forecasting accuracy is measured by calculating the MAPE of the forecasted period. Figure 8.18 shows the forecasting accuracy of the four models for the Domestic, the Non-Domestic and the Total consumption.

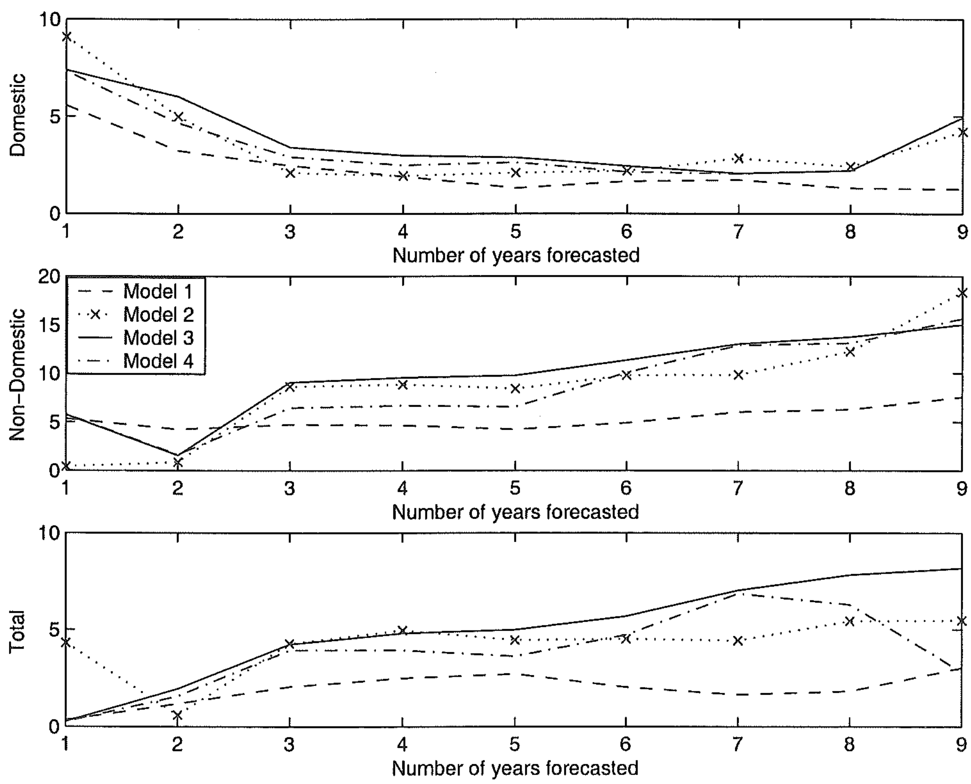

Figure 8.18 Forecasting accuracy of the various VAL models for the United States

In all cases Model 1 has given the best forecasts in general. This result, along with the results in Section 8.8.2 shows that the best VAL model is the one in which the saturation levels are estimated by the combination of GDP and population.

Therefore, the proposed VAL model for the Domestic sector is

$$f_D = \frac{F_D(X)}{1 + \exp(-177 + 0.099t)} \tag{8.14}$$

And that for the Non-Domestic sector is

$$f_{ND} = \frac{F_{ND}(X)}{1 + \exp(-147 + 0.074t)} \tag{8.15}$$

And that for the Total electricity consumption is

$$f_T = \frac{F_T(X)}{1 + \exp(-154 + 0.079t)} \tag{8.16}$$

In all cases the variable saturation levels $F_D(X)$, $F_{ND}(X)$ and $F_T(X)$ are estimated using GDP and population and are of the form

$$F(X) = a_0 + a_1 X_1 + a_3 X_2 \tag{8.17}$$

where,

X_1 is GDP, and

X_2 is population.

The variables a_0, a_1 and a_3 are the multiple linear regression coefficients calculated separately for each of the Domestic, the Non-Domestic and the Total electricity consumptions. These models will be referred to as the VAL models for the USA.

8.8.4 VAL Model Forecasts

Figure 8.19 shows the saturation levels obtained by the Fibonacci search technique and those estimated by the VAL models for the Domestic, the Non-Domestic and the Total electricity consumption. The saturation levels obtained by the Fibonacci search technique are very well estimated by the VAL models.

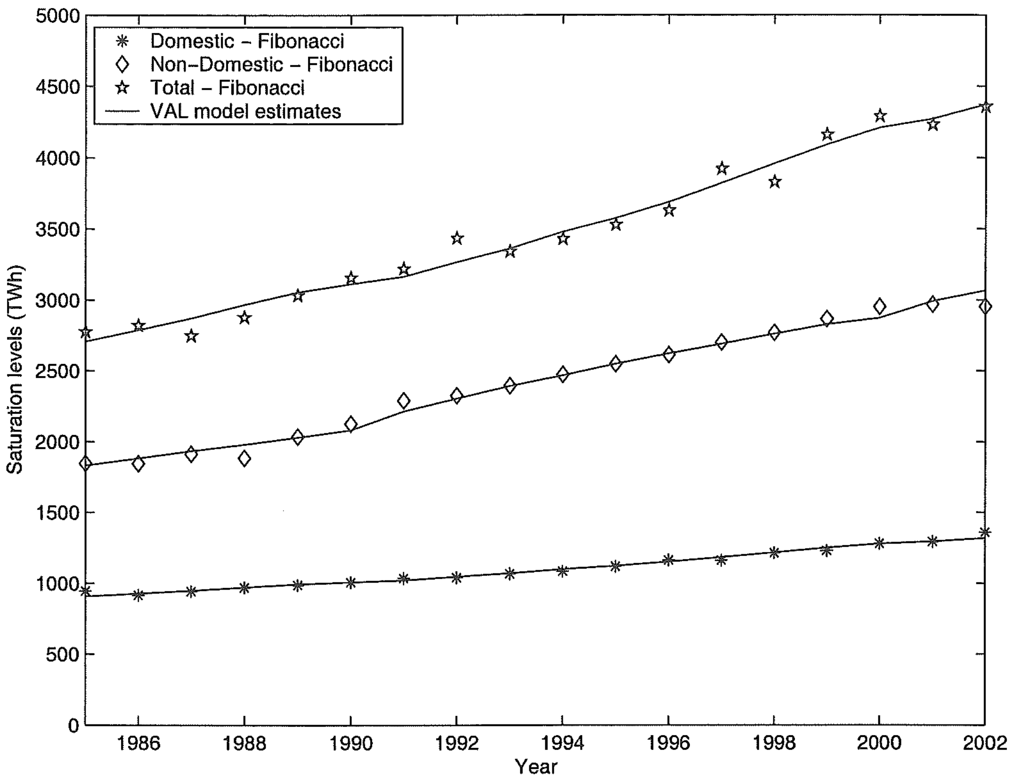

Figure 8.19 Saturation level estimated by the VAL models

The forecasting accuracies of the VAL models are compared with those of the original Logistic model. Figure 8.20 shows the forecasting accuracies of the VAL models and the Logistic models for the Domestic, the Non-Domestic sectors and the Total electricity consumption for the United States. The VAL model has given more accurate forecasts than the Logistic model except for the first four years of the Non-Domestic consumption. The accuracy in the Domestic and the Total consumptions are significantly better than the Logistic model where the VAL models have given consistently low forecasting errors over the whole period compared. Therefore the VAL model is accepted for forecasting electricity consumption in the United States.

8.9 COMPARISON OF THE MODELS

8.9.1 Comparison of Model Fit and Forecasting Accuracy

The forecasting accuracy for the United States is calculated using MAPE. The MAPE values are calculated from 1 year ahead forecasts to 9 years ahead forecasts. That is, accuracy is measured by subsequently holding out actual data from 1994 (9 years ahead) to 2002 (1 year ahead). Figure 8.21 shows the forecasting accuracy of all the models for the Domestic, the Non-Domestic and the Total electricity consumption for the United States.

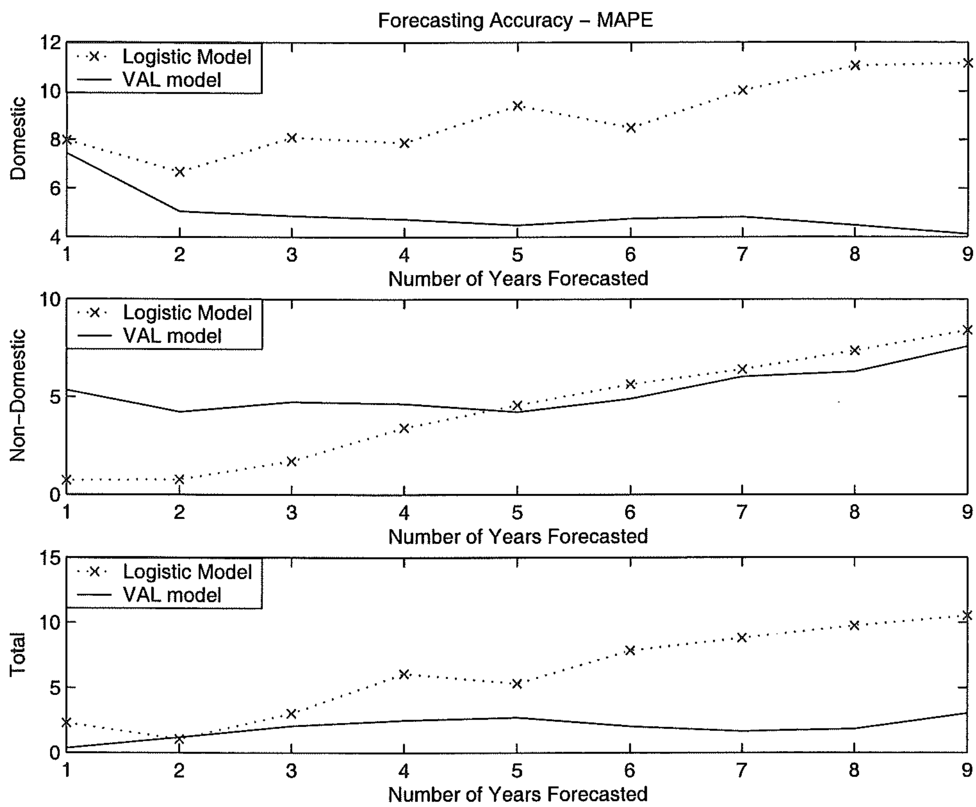

Figure 8.20 Comparison of forecasting accuracies of the VAL model and Logistic model

To compare the forecasting accuracy, the nine year period is divided into short term (1-3 years), medium term (4-6 years) and long term (7-9 years) forecasts as for New Zealand. The models are ranked from 1 to 6 (1= best model, 6 = worst model). The best model is the model with either the best fit or the best forecasting accuracy. The rankings of the models in terms of the model fit and forecasting accuracy for the Domestic, the Non-Domestic and the Total electricity consumption given by the six developed models for the United States are shown in Table 8.6. The best model fits in all cases are given by the Harvey model, followed by the Harvey Logistic and then by the ARIMA models. In all cases, the worst fit is given by the Logistic model.

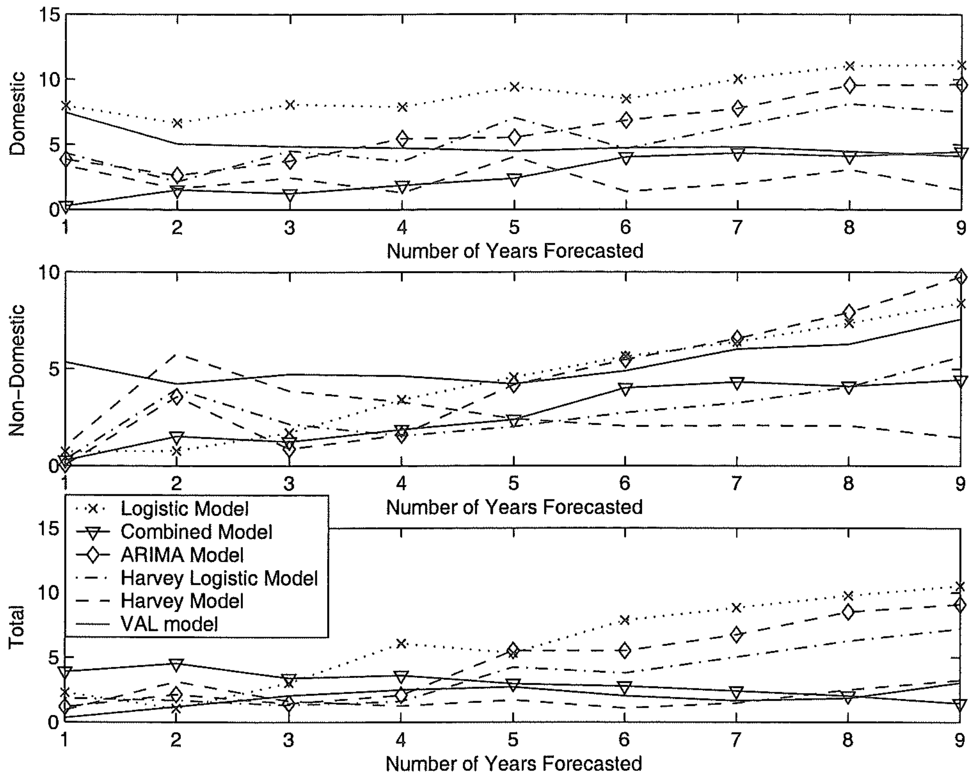

Figure 8.21 Forecasting accuracies of all models for the United States

Table 8.6 Rankings of the models developed for the USA (1 = best model, 6 = worst model)

Model	Domestic					Non-Domestic					Total				
		Forecast accuracy					Forecast accuracy					Forecast accuracy			
	fit	Short	medium	long	**Overall**	fit	Short	medium	long	**Overall**	fit	Short	medium	long	**Overall**
Logistic	6	6	6	6	**6**	6	1	5	5	**4**	6	5	6	6	**6**
Combined	5	1	2	2	**2**	4	5	3	1	**3**	5	6	3	1	**3**
ARIMA	3	3	5	5	**5**	3	2	4	6	**5**	3	2	5	5	**5**
Harvey Logistic	2	4	4	4	**4**	2	3	1	3	**2**	2	3	4	4	**4**
Harvey	1	2	1	1	**1**	1	4	2	2	**1**	1	4	1	3	**1**
VAL	4	5	3	3	**3**	5	5	6	4	**6**	4	1	2	2	**2**

For the Domestic sector, the best short term forecast is given by the Combined model and the second best accuracy is given by the Harvey model. The best medium term and long term Domestic forecasts are given by the Harvey models while the Combined models gave the second best medium term and long term forecasts. The Logistic models gave the worst forecasts in all cases of the Domestic electricity consumption. In general, the best overall forecasts for the Domestic consumption are given by the Harvey model.

For the Non-Domestic sector, the best short term forecast is given by the Logistic model, medium term by the Harvey model and long term by the Combined model. The second best Non-Domestic short term forecast is given by the ARIMA model, while Harvey models gave the second best medium term and long term forecasts. In general, the best overall forecasts for the Non-Domestic sector are given by the Harvey model, while the VAL model is ranked the worst overall model.

For the Total consumption, the best short term forecast is given by the VAL model, medium term by the Harvey model and long term by the Combined model. The second best short term forecast is given by the ARIMA model, while the second best medium and long term forecasts are given by the VAL models. The Harvey model is once again ranked the best overall model followed by the VAL model. The Logistic models continued to give the worst overall forecasts in the Total consumption.

8.9.2 Comparison of Forecasts

The forecasts obtained by the six developed models for the United States are compared. Figures 8.22 to 8.24 show the forecasts of the six developed models from 2003 to 2017 for the Domestic, the Non-Domestic and the Total electricity consumption respectively. In the Domestic sector, the forecasts given by the Combined model, the ARIMA model and the Harvey model are very similar in that they are almost indistinguishable in Figure 8.22. The VAL model also gave forecasts that are very close to these forecasts, especially in the later years. The Logistic model, followed by the Harvey Logistic model, gave the lowest Domestic consumption forecasts. The forecasts in the Non-Domestic sector are more spread out than those for the Domestic sector. The lowest forecasts are given by the Harvey Logistic and Logistic models while the highest forecasts are given by the VAL model. The forecasts by the other three models are somewhere in between these forecasts. The forecasts for the Total consumption followed a similar pattern to those for the Non-Domestic electricity consumption.

The forecasts of the Total electricity consumption in the United States for the years 2005, 2010 and 2015 are published by the Energy Information Administration (EIA) [EIA_2, 2003]. Table 8.7 shows the forecasts of EIA along with the forecasts given by the six developed models for the United States.

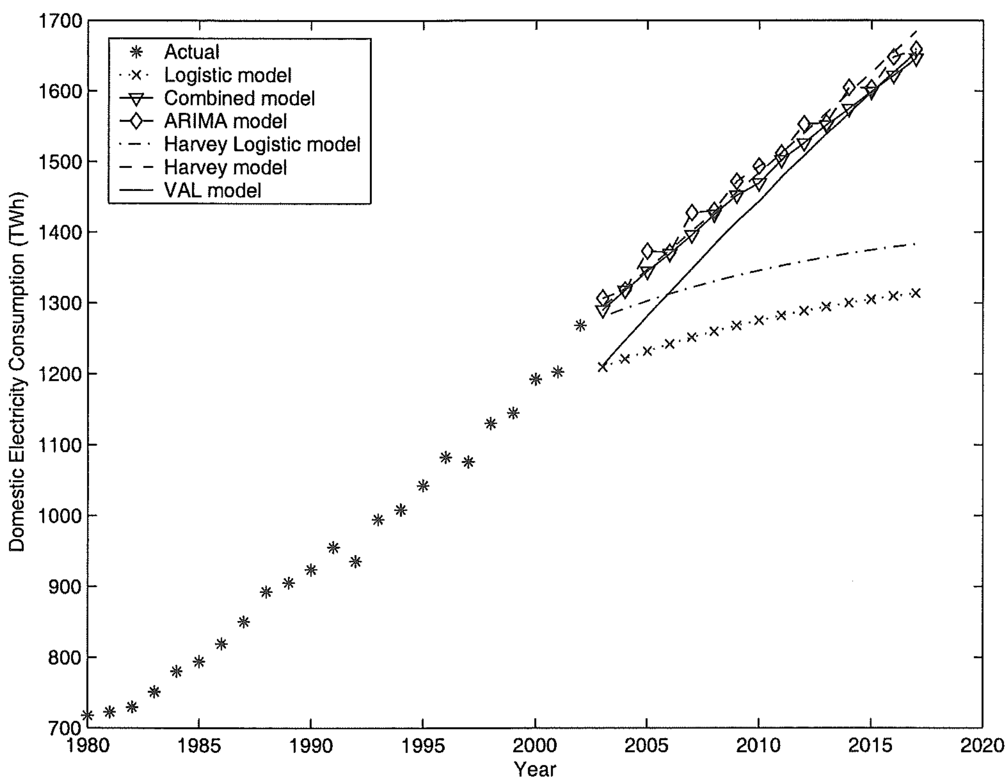

Figure 8.22 Comparison of Domestic forecasts by all the developed models for the USA

The EIA projection for 2005 is lower than those predicted by all the developed models. However, all models except the Combined and VAL models have given forecasts that are close to the EIA forecasts. For 2010, the closest forecasts to the EIA are given by the ARIMA model, while close forecasts are also given by the Logistic, the Harvey Logistic and the Harvey models. Even for 2015, the forecast by the ARIMA is almost equal (0.3% difference) to the projections by the EIA while the next closest forecast is given by the Harvey model.

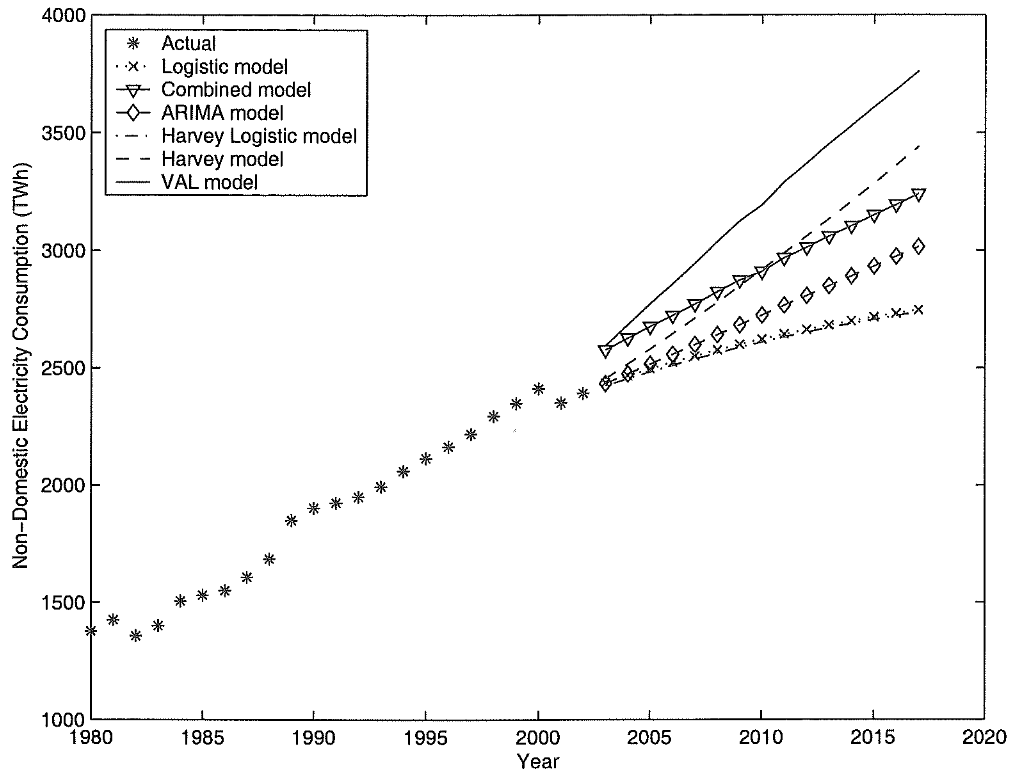

Figure 8.23 Comparison of Non-Domestic forecasts by all the developed models for the USA

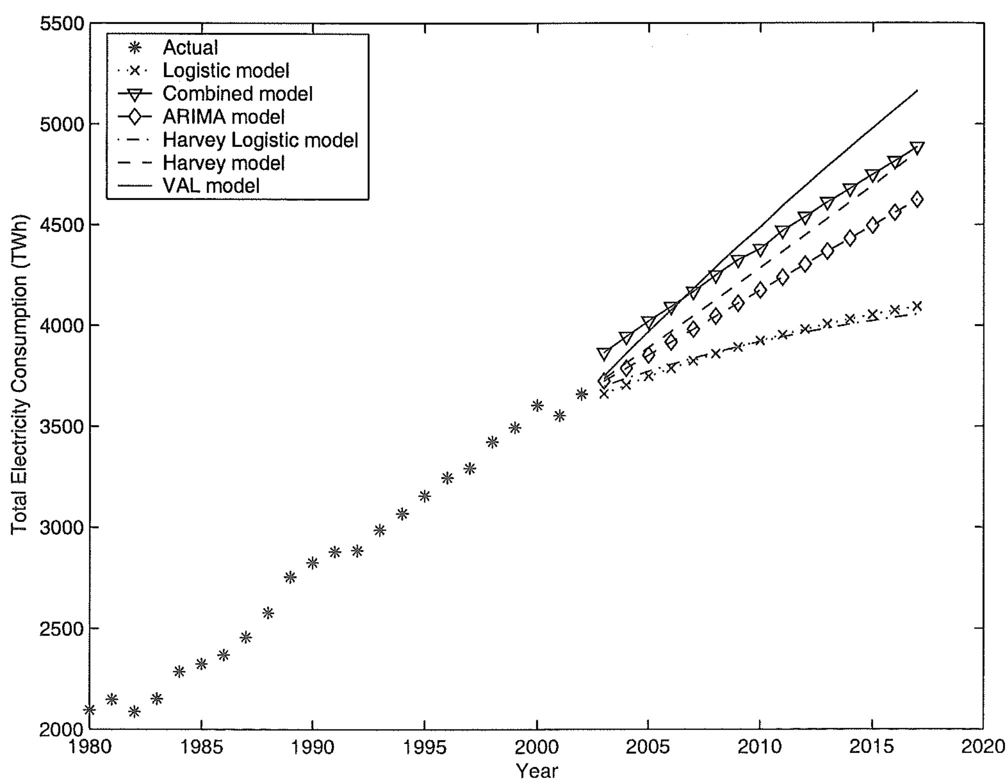

Figure 8.24 Comparison of Total consumption forecasts by all the developed models for USA

Table 8.7 Comparison of EIA projections with the developed models for Total electricity consumption

Model	*2005*		*2010*		*2015*	
	TWh	*%Difference*	*TWh*	*%Difference*	*TWh*	*%Difference*
EIA	3684	-	4101	-	4481	-
Logistic	3747	1.71	3924	-4.32	4053	-9.55
Combined	4021	9.15	4379	6.78	4749	5.98
ARIMA	3853	4.59	4174	1.78	4495	0.31
Harvey Logistic	3773	2.42	3920	-4.41	4024	-10.20
Harvey	3891	5.62	4286	4.51	4694	4.75
VAL	3971	7.79	4487	9.41	4979	11.11

Overall, according to the forecasting accuracy measurements in Section 8.9.1, the best model is the Harvey model and the ARIMA model is ranked the second worst model for the United States. However, the forecasts given by the ARIMA model, which has produced the second worst forecasting accuracy, are in close agreement with the EIA projections indicating that the EIA forecasts may involve such a technique. The forecasts given by the most accurate Harvey models are also not very far from the EIA projections.

8.10 SUMMARY

In this chapter, a brief overview of electricity development in the United States of America has been initially described. The proposed electricity forecasting models are applied to the electricity consumption data of the United States. All the developed models generally gave acceptable fits to the historical electricity consumption data. In the Combined model it was found that the combination of GDP and population of the United States gave the best results. In addition, the best VAL model also used these variables.

Comparison of model fit and forecasting accuracy showed that the Harvey model was the best in model fit as well as the best overall forecasting in the Domestic, the Non-

Domestic and the Total electricity consumption of the United States. In addition, it was also found that the worst forecasting accuracies are given by the Logistic model, followed by the ARIMA model. While the ARIMA model was among the worst in forecasting accuracy, their forecasts were found to be very close to the national forecasts available in the United States. The forecasts given by the best Harvey models are also within comparable values to the national forecasts in the United States.

Chapter 9

FORECASTING ELECTRICITY CONSUMPTION IN THE UNITED KINGDOM

9.1 INTRODUCTION

The United Kingdom produces and exports the largest amount of petroleum in the European Union. Apart from being the largest natural gas producer in the European Union, the United Kingdom is also one of the largest energy consumers in Europe [EIA_4, 2004]. While the overall final energy consumption in the United Kingdom has increased by 10 percent from 1970 and by 9 percent since 1990, the electricity consumption has increased by 74 percent over the period 1970 to 2001 [DTI_1, 2004]. This reflects a steady growth of about 1% in final energy consumption and 2% in electricity per year over the last 20 years. In 2002, the United Kingdom had an installed electric generating capacity of 77 GW, of which 80 percent was thermal, 16 percent nuclear, 2 percent hydropower and 2 percent other sources [EIA_4, 2004]. The total electricity consumed in the United Kingdom in 2002 was 243.8 TWh [DTI_2, 2004].

This chapter initially describes a brief overview of the history and current structure of the electricity industry in the United Kingdom. The proposed electricity forecasting models are applied to the United Kingdom's electricity consumption data from 1965 to 2002. The developed models are compared using model fit and forecasting accuracy as for the other countries. Finally, the chapter is concluded with comparison of forecasts.

9.2 ELECTRICITY INDUSTRY IN THE UNITED KINGDOM

9.2.1 Structure Prior to Privatisation

Since the beginning of the United Kingdom's electricity industry in the late nineteenth century, the central government's role in electricity gradually increased [EIA, 1997]. In 1882, the Electricity Lighting Act allowed the central government to break up streets for the laying of electric cables. In 1926, an Electricity Generation Board was established to construct a national transmission grid, to coordinate the transmission of electricity across the country and to establish a set of common technological standards [EIA, 1997]. In 1947, the electricity industry was nationalised by the post-war labour government. The nationalised electricity company included most of the generation capacity, the national grid and 12 semi-autonomous regional distribution boards in England and Wales and one other company each in Scotland and Northern Ireland [EIA, 1997].

The Electricity Act of 1957 further extended the role of the central government in electricity. A Central Electricity Generating Board (CEGB) was established to control the operation of electricity generation and transmission facilities and all related investment decisions [EIA, 1997]. Since the 1950's, nuclear power was promoted by the United Kingdom government as a secure and economical source of electricity. Although nuclear power was perceived as an economically viable form of achieving energy security, its full costs have far exceeded the costs of non-nuclear forms of electricity [EIA, 1997]. The government made several attempts to reform electricity industry in the 1960's and the 1970's. However, they were unsuccessful mainly due to the lack of commitment and political turnover.

9.2.2 Privatisation and Current Structure

The Electricity Act of 1983 that was designed to encourage the growth of independent power producers was one of the first steps towards electricity reform [EIA, 1997]. The Act not only allowed the entry of independent power producers to the electricity industry but also required the CEGB to purchase electricity from private producers at price equal to costs the board would produce the same quantity itself. The 1983

Electricity Act did not completely remove the unfair access that incumbent power producers had over new entrants [EIA, 1997]. Thus, this was regarded as a minor first step toward privatising and deregulating electricity in the United Kingdom.

The Electricity Act of 1989 allowed for the restructuring of industry prior to its sale [EIA, 1997]. The CEGB was initially restructured into four separate organisations. They included two power producers, a transmission company, and a distribution network that consisted of twelve regional electricity companies. The ownership of the national grid was initially transferred to the regional electricity companies upon their privatisation [EIA, 1997]. The restructuring of Northern Ireland and Scotland took place around the same time as the industries in England and Wales.

The Electricity Act 1989 also allowed the customers to choose their own suppliers [EIA, 1997]. This was introduced in three stages [DTI_3, 2004]. Firstly from 1 April 1990, customers with a peak load of more than 1 MW were able to choose their supplier. Secondly, from 1 April 1994, customers with peak loads of more than 100 kW were allowed to choose their supplier. Thirdly, between September 1998 and May 1999, the remaining electricity market was open to competition [DTI_3, 2004]. Over the years, restructuring of the electricity industry has resulted in a number of mergers and acquisitions.

The New Electricity Trading Arrangements (NETA), introduced in March 2001, again changed the structure of the electricity industry [EIA_4, 2004]. Previously, the generators and suppliers in England and Wales traded electricity through an electricity pool. This was regulated by the National Grid Company, owner of the transmission network. The NETA transformed the pool into a wholesale electricity market, based on bilateral trading among generators, suppliers, traders and customers [EIA_4, 2004]. The introduction of NETA dropped the electricity prices in the United Kingdom significantly. Although this benefited the customers, some companies struggled to remain solvent. Currently, Scotland operates its own electricity market while England and Wales have a common market. The government has begun reviewing a new Energy Bill that seeks to create a common set of trading rules so that electricity can be traded freely across Great Britain [EIA_4, 2004].

9.2.3 Electricity Consumption in the United Kingdom

Figure 9.1 shows the electricity consumption for the United Kingdom from 1965 to 2002. The data are divided into the Domestic and the Non-Domestic sectors similar to those for New Zealand, the Maldives and the United States. These data are obtained from the Department of Trade and Industry [DTI_4, 2004] and the Energy Information Administration [EIA, 1997]. Appendix A gives details of these values.

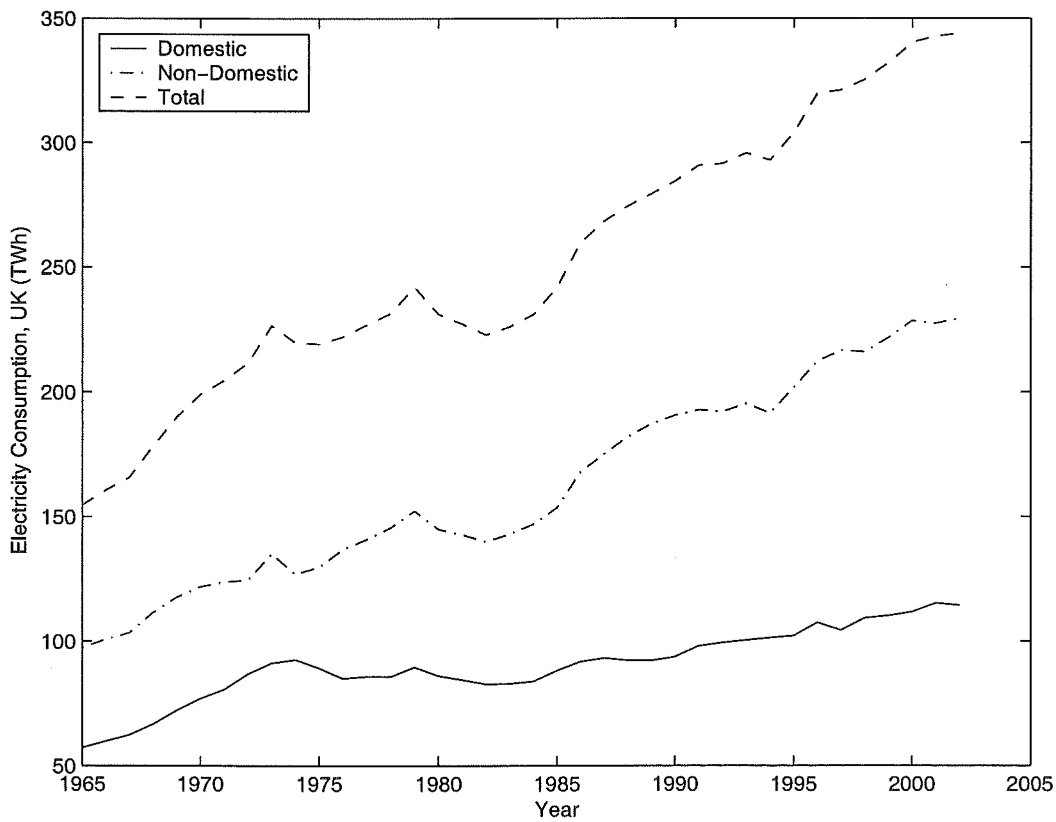

Figure 9.1 Electricity consumption in the United Kingdom from 1965 to 2002

The electricity consumption pattern for the United Kingdom has varied very differently from those of the other countries presented so far. The pattern is very irregular with peaks at 1973 and 1978. The large decreases in consumption from 1978 to mid 1980's are possibly due to increases in electricity prices, several currency crises and two major oil shocks in the 1970s and 1980's [EIA, 1997]. While the Domestic sector shows smaller variations in consumption than the Non-Domestic sector, the Non-Domestic sector shows a faster rate of growth in electricity consumption.

9.3 THE LOGISTIC MODEL

For each of the Domestic, the Non-Domestic and Total electricity consumption data, the Fibonacci search technique [DTI_5, 2004] is applied to obtain the asymptotes *F*. The respective asymptotes are then used in the developed Logistic model program to obtain forecasts of electricity consumption. The fits of the Logistic models to the historical data are shown in Figures 9.2 for the Domestic, the Non-Domestic and the Total electricity consumption.

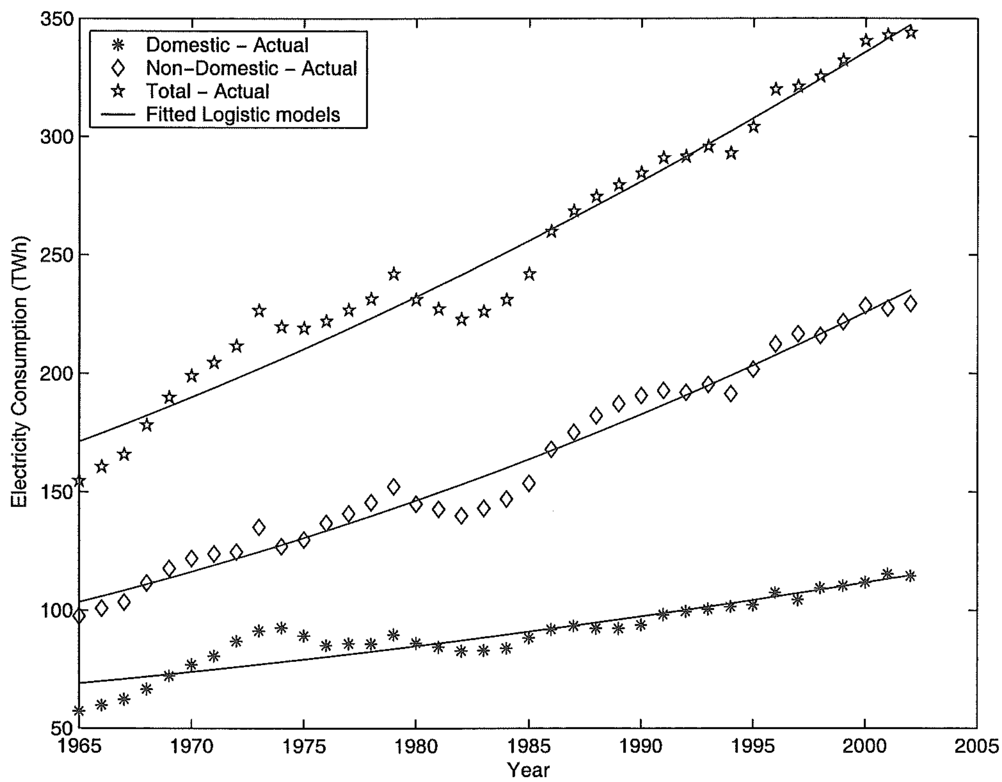

Figure 9.2 Fitted Logistic models for electricity consumption in the UK

The figures show some significant deviations from the actual consumption values in the early years, especially for the years where there were sudden changes in consumption. The consumption estimates in the latter years in all cases are very close. The mean absolute percentage error (MAPE) values are 5.18, 3.38 and 3.67 for the Domestic and the Non-Domestic sectors and the Total electricity consumption respectively. This suggests that the fit in the Domestic sector is worse than the Non-Domestic and the Total electricity consumptions. Although these fits seem too far from the actual consumption values, the Logistic model will be retained to compare with the other applied models for the United Kingdom. On the other hand, the model could not be discarded before analysing how well the model estimates the forecasts.

9.4 THE COMBINED MODEL

In the Combined model, a multiple linear regression technique is used to model electricity consumption in the United Kingdom using gross domestic product (GDP) and population. The GDP data are obtained from the Department of Trade and Industry [DTI_5, 2004], and the population data are obtained from the Office for National Statistics [Office for National Statistics, 2004] and Mitchell [Mitchell, 1988]. Details can be found in Appendix A. The GDP data, expressed in billions of £, are at 1995 market prices [DTI_5, 2004]. Although the consumption data are available from 1965, the GDP and population data are only available from 1970. Thus, in the Combined model all data from 1970 to 2002 are used.

Correlation coefficients show the strength of the relationship between the selected variables and the electricity consumption. The correlation coefficients between the selected GDP and population to the electricity consumption are given in Table 9.1. The correlation coefficients of GDP and population are very high for all cases of electricity consumption. Therefore, both the variables are used in developing the Combined models.

Table 9.1 Correlation coefficients between the variables and electricity consumption in the UK

	Domestic	Non-Domestic	Total	GDP	Population
Domestic	1			0.946	0.969
Non-Domestic		1		0.988	0.971
Total			1	0.990	0.983
GDP				1	0.987
Population					1

Thus, the proposed Combined model for the United Kingdom is

$$Y = a + b_1 X_1 + b_2 X_2 \tag{9.1}$$

where,

Y is the electricity consumption in TWh,

X_1 is GDP (in billions of pounds),

X_2 is population, and

a, b_1 and b_2 are constants.

The models obtained by the multiple linear regression technique are tested for the statistical strengths using the adjusted coefficient of determination r^2, F-test and t-test [Makridakis *et al.*, 1998]. The results along with the critical values are shown in Table 9.2.

Table 9.2 Statistical validity test results for the UK

	adjusted	F- test		t -test		
	r^2	99% value	F	99% value	t_1	t_2
Domestic	0.880	5.49	213	2.47	-8.00	28.91
Non-Domestic	0.948	5.49	518	2.47	36.30	-3.6
Total	0.960	5.49	680	2.47	28.9	8.8

In all cases the adjusted coefficients of determination are high, indicating that the variance in electricity consumption is well explained by the combination of GDP and population for the United Kingdom. Thus, it is expected that those consumption models, with good forecasts of the variables, should produce good forecasts of the electricity consumption. In all cases of the F-tests the 99% critical values are much lower than the value of F obtained for the models. These indicate that the variables in the models are significant. In the individual testing of the coefficients using the t-tests, the absolute value of the t-test results t_1 and t_2 for the coefficients of X_1 and X_2 are higher than the 99% critical value of t in all cases. This implies that coefficients b_1 and b_2 are significantly different from zero for each of those models. The residuals produced by the models are also studied. Figure 9.3 shows the residuals produced by the Total consumption model against the fitted values and variables.

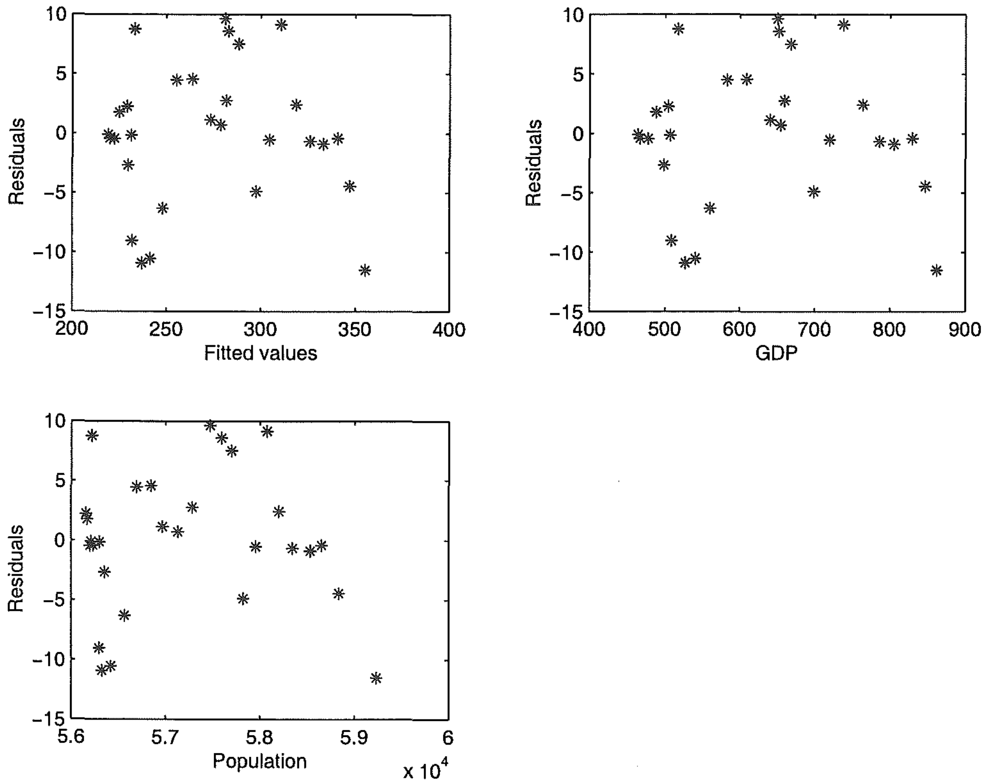

Figure 9.3 Residuals against the fitted variables of the Combined model

There is no apparent pattern in any of the plots. This shows that the residuals are white noise. These results along with the validity test results and the correlation coefficients suggest that a multiple linear regression model using GDP and population should produce acceptable models. Therefore, the developed Combined model is used to forecast electricity consumption in the United Kingdom.

Figure 9.4 shows the Combined model fits to the historical consumption data for the Domestic, the Non-Domestic and the Total electricity consumption. The Combined models have given very good fits of the historical data with very low MAPE values of 2.33, 2.20 and 1.57 for the Domestic, the Non-Domestic and the Total electricity consumption respectively. The error in the Domestic sector is possibly higher as the variations in consumption in the Domestic sector are large in the early years as compared to the Non-Domestic and the Total electricity consumption.

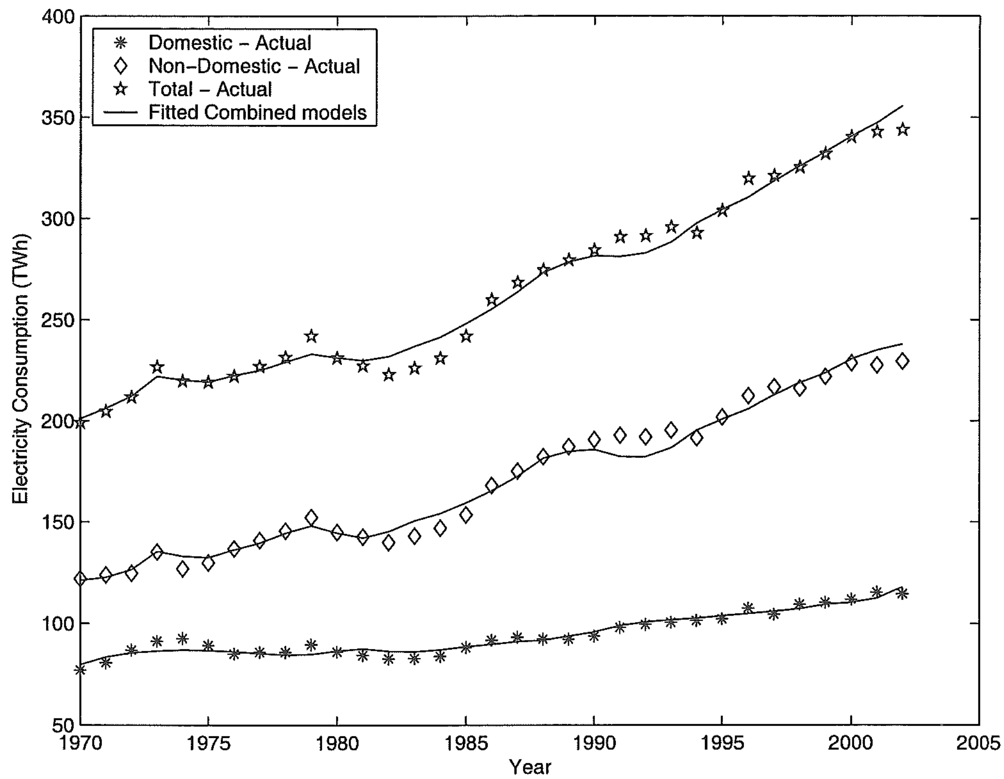

Figure 9.4 Fitted Combined models for electricity consumption in the UK

9.5 THE ARIMA MODELS

The steps of identification, estimation, diagnostic testing and forecasting involved in the ARIMA process [Makridakis *et al.*, 1998] have been applied to the Domestic, the Non-Domestic and the Total electricity consumption data of the United Kingdom.

9.5.1 Domestic ARIMA Model

The process of identification involves making the series stationary. This is done by differencing the series and observing the autocorrelation (ACF) plots and partial autocorrelation plots [Makridakis *et al.*, 1998]. Figure 9.5 shows the ACF and PACF plots of the original Domestic data.

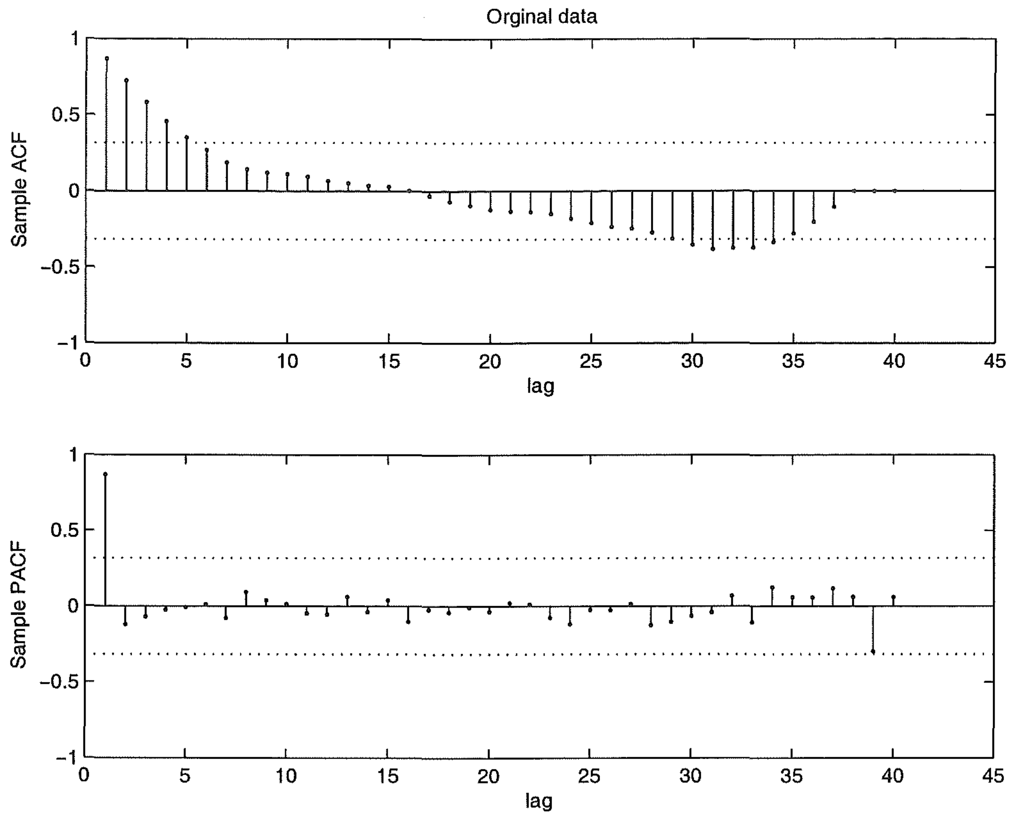

Figure 9.5 ACF and PACF of the original Domestic data for the UK

The series is not stationary as a significant number of correlations are outside the limits of stationarity shown by the dotted lines. This is also supported by the very high PACF at lag 1. The data is therefore differenced at lag 1. The resulting ACF and PACF plots are shown in Figure 9.6. All correlations except one coefficient at lag 18 of the PACF plot are well within the limits of stationarity. This satisfies the condition of stationarity as the coefficients are within the limits more than 95% of the time. Attempting to difference the series any more did not improve the results. The best model to fit the stationary series is identified by the software ITSM2000, using the criteria of the lowest AICC value [Brockwell and Davis, 2002]. The best selected model is the ARIMA(0,1,2) model.

The maximum likelihood estimation of the model is

$$Y_t' = e_t + 0.355e_{t-1} + 0.623e_{t-2} \tag{9.2}$$

where e_t is approximated by a zero mean white noise (WN) sequence, i.e. e_t ~ WN(0, 5.69). Since the data is differenced and mean corrected before estimation, $Y_t' = Y_t - Y_{t-1} - 1.55$ and thus

$$Y_t = 1.55 + Y_{t-1} + e_t + 0.355e_{t-1} + 0.623e_{t-2} \qquad (9.3)$$

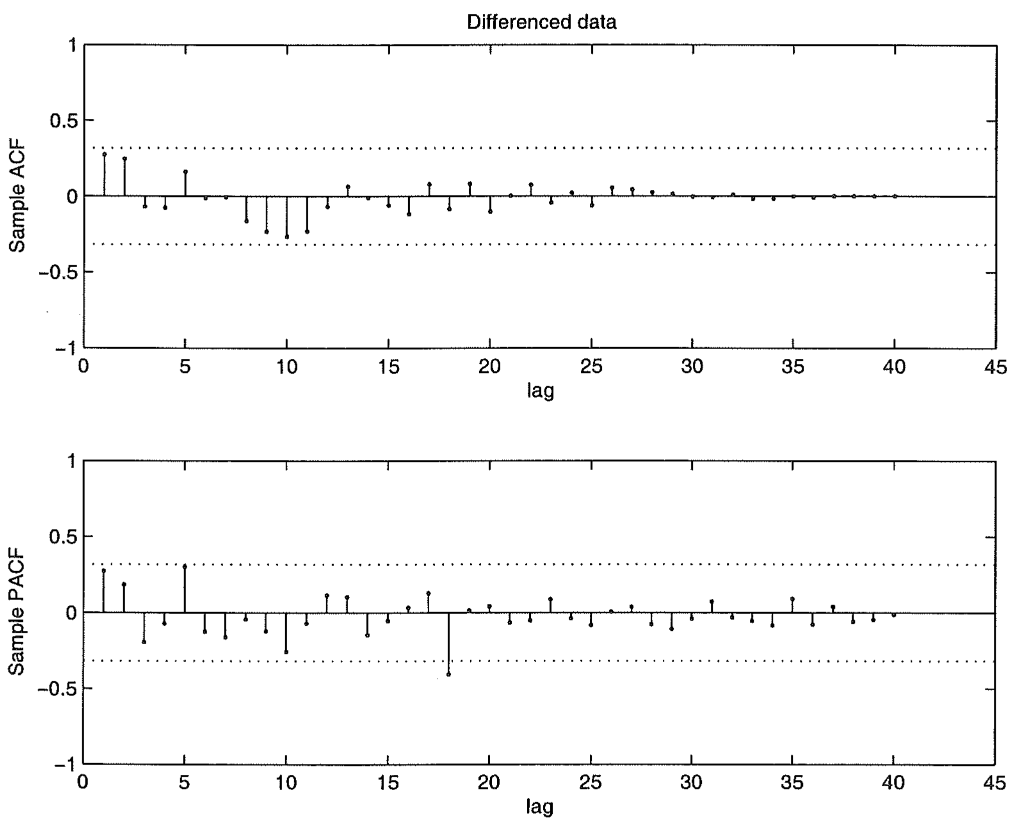

Figure 9.6 ACF and PACF of differenced Domestic data

The model fit given by the estimated ARIMA(0,1,2) model for the Domestic sector is shown in Figure 9.7. The ARIMA(0,1,2) has produced a very good estimate of the historical Domestic data. However, acceptance of this model depends on the ability of the model to satisfy the diagnostic tests.

Figure 9.8 shows the ACF and PACF plots of the residuals produced by this model.

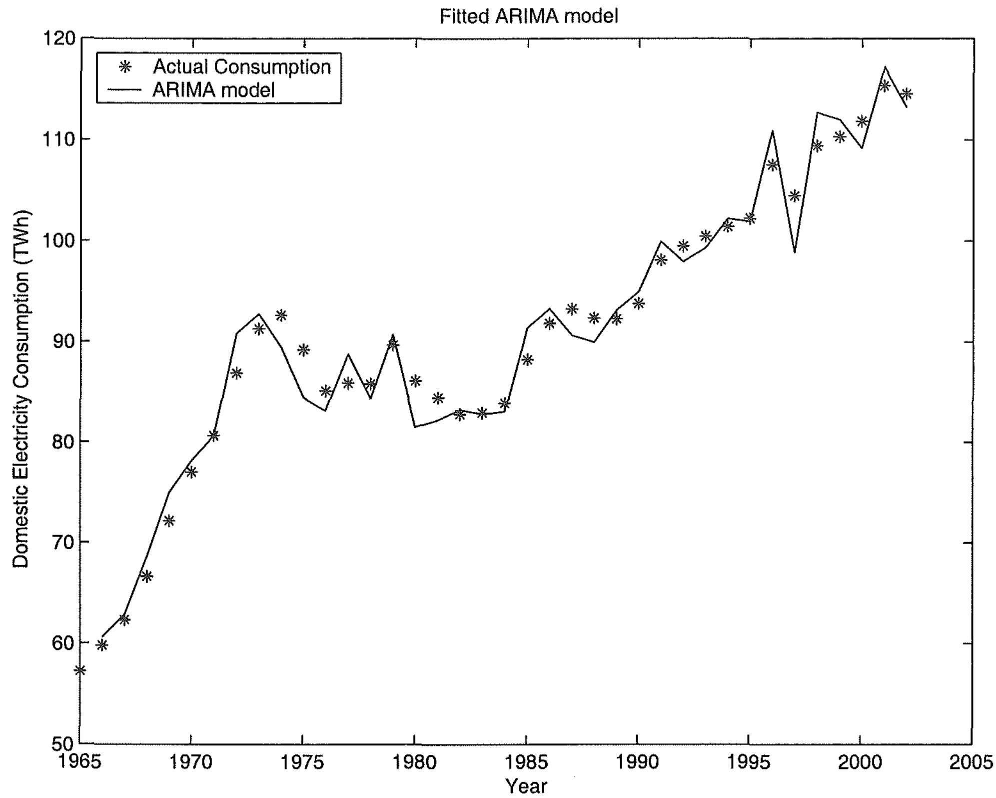

Figure 9.7 Fitted ARIMA model for the Domestic sector of the UK (MAPE = 2.17)

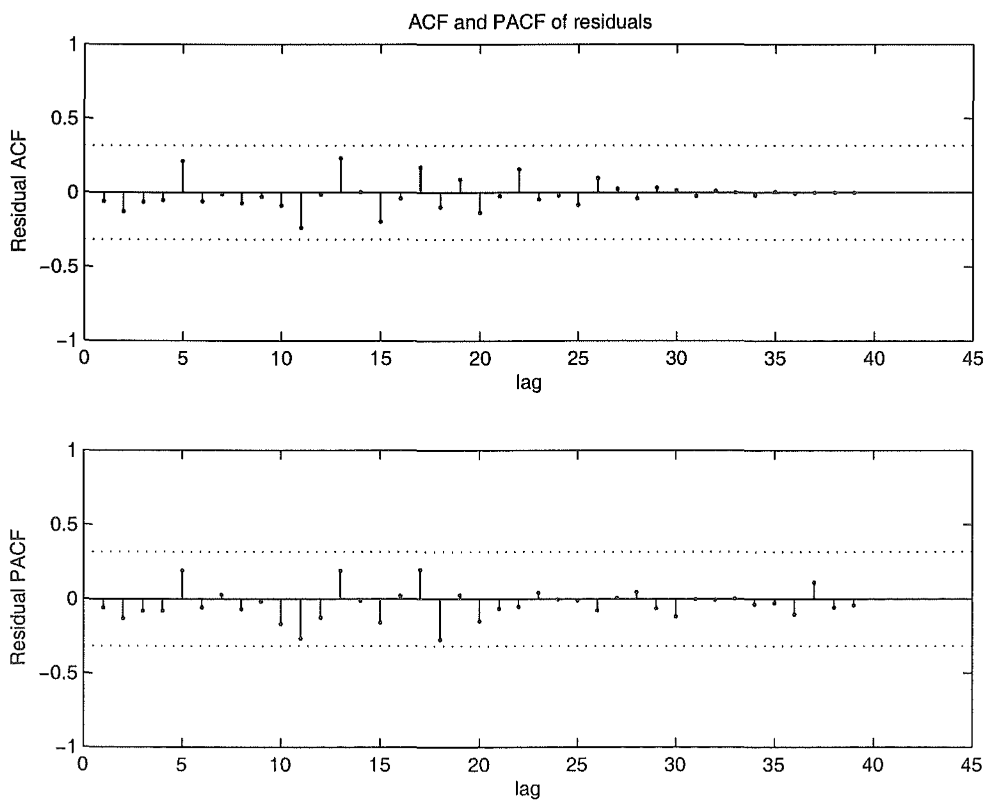

Figure 9.8 ACF and PACF of the residuals for the Domestic sector

The coefficients of the residuals are well within the stationarity limits indicating that the residuals are white noise. Further more, the Ljung-Box Q statistic [Brockwell and Davis, 2002] gives a Q value of 20.4. This is much lower than the corresponding critical chi-square of 31.41 at the 95% probability level suggesting that the residuals produced by the ARIMA(0,1,2) model are not significant. Having passed the diagnostic tests the ARIMA(0,1,2) model is proposed for forecasting the Domestic electricity consumption in the United Kingdom.

9.5.2 Non-Domestic ARIMA Model

The ACF and PACF plots of the Non-Domestic sector data are shown in Figure 9.9. Clearly, the series is not stationary. Thus, the data is differenced at lag 1. The corresponding ACF and PACF plots of the differenced data are shown in Figure 9.10. The ACF and PACF plots are now well within the limits of stationary. The best ARIMA model identified using ITSM2000 is the ARIMA(0,1,0) model.

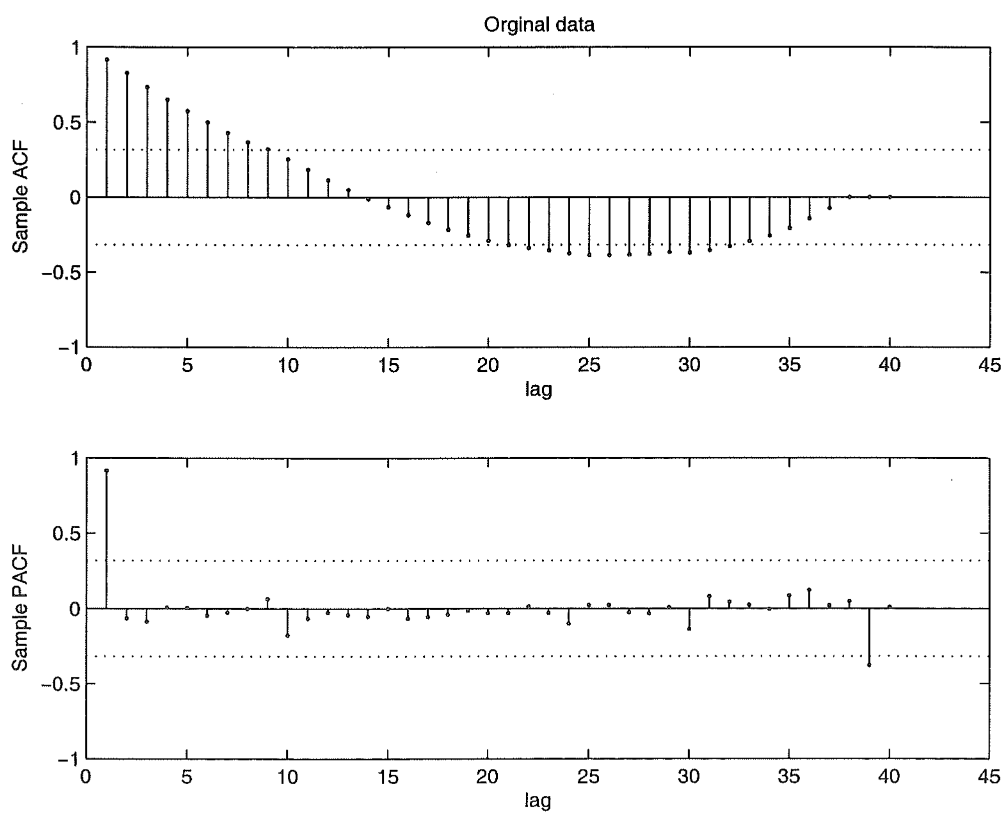

Figure 9.9 ACF and PACF plots of original Non-Domestic data for the UK

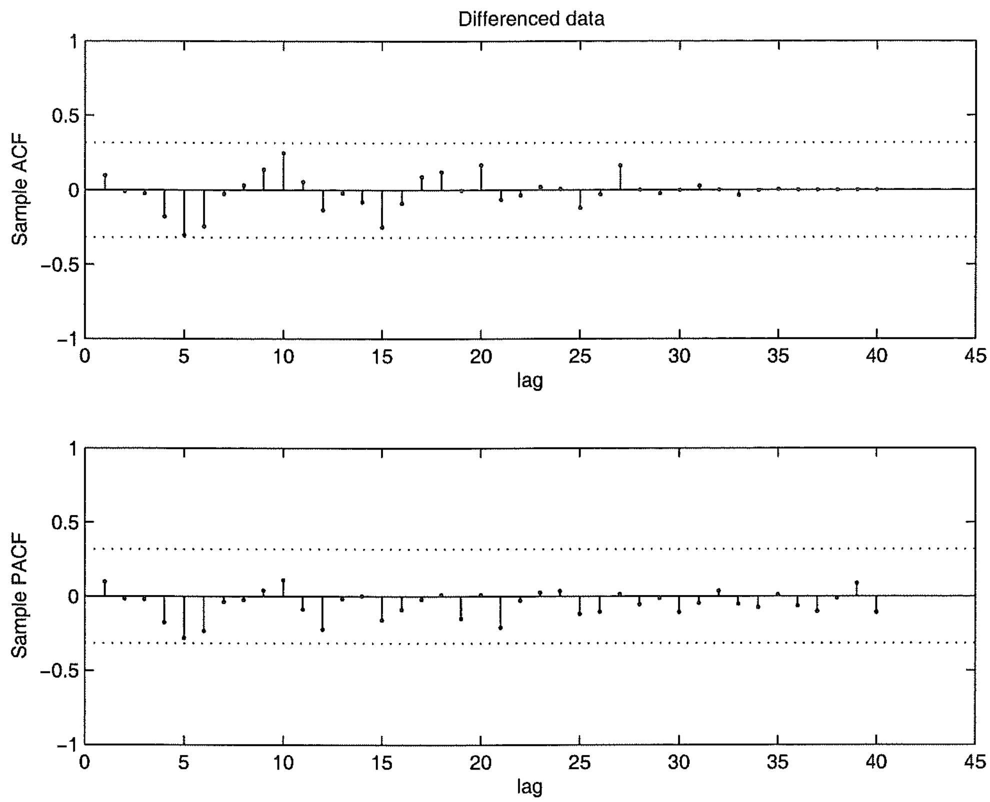

Figure 9.10 ACF and PACF of the differenced Non-Domestic data

The maximum likelihood estimate of the model is

$$Y_t' = e_t \qquad (9.4)$$

where e_t is approximated by a zero mean white noise (WN) sequence, i.e. e_t ~ WN(0, 22.2).

Since the data is differenced and mean corrected before estimation, $Y_t' = Y_t - Y_{t-1} - 3.56$ and thus

$$Y_t = 3.56 + Y_{t-1} + e_t \qquad (9.5)$$

The estimates of the Non-Domestic consumption given by the estimated ARIMA(0,1,0) model is shown in Figure 9.11, while the corresponding ACF and PACF of the residuals are shown in Figure 9.12

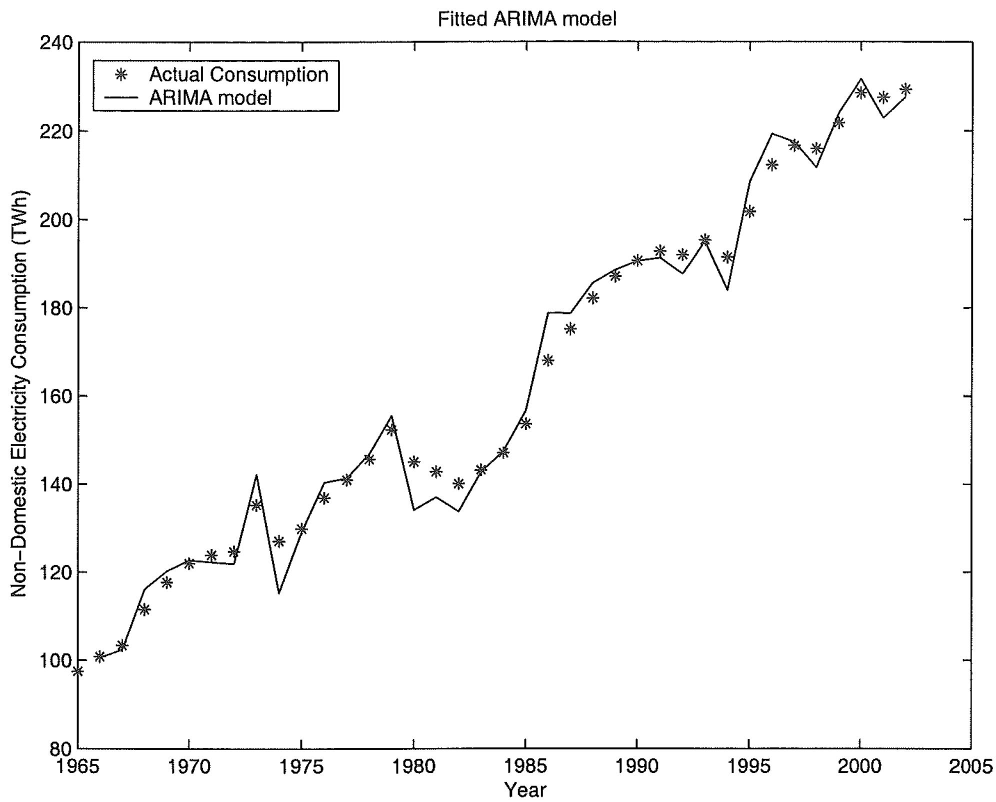

Figure 9.11 Fitted ARIMA model for the Non-Domestic sector of the UK (MAPE = 2.25)

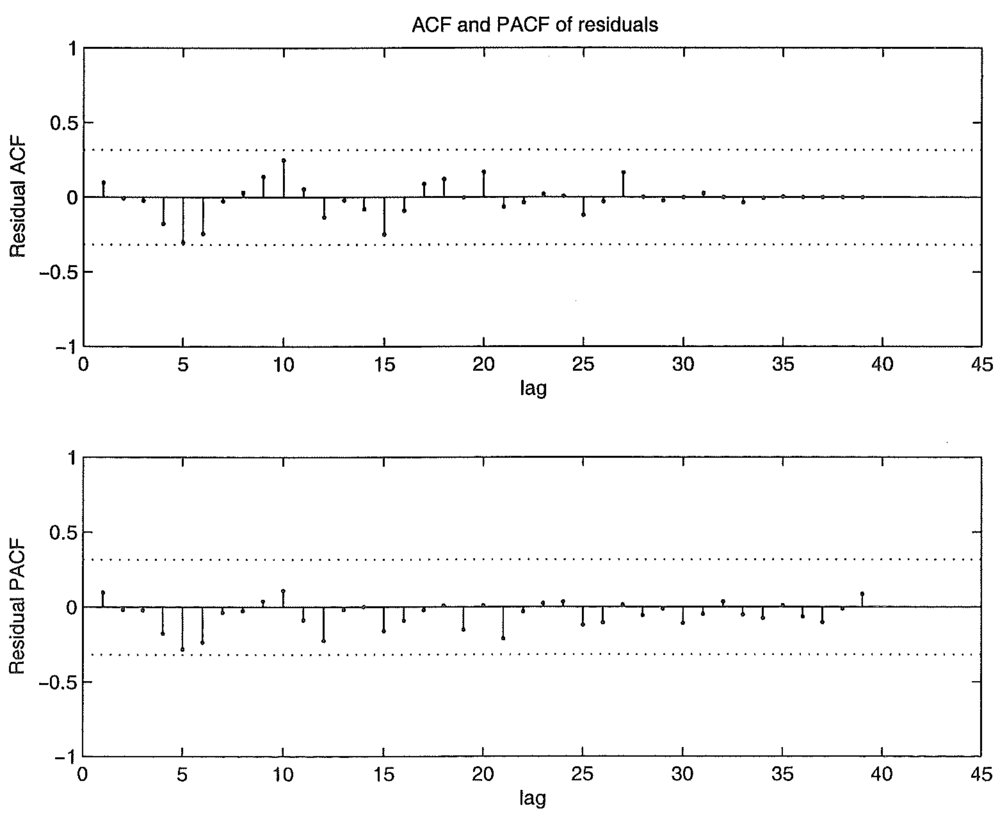

Figure 9.12 ACF and PACF of the residuals for the Non-Domestic model

The ARIMA (0,1,0) has given a similar fit to the historical data as for that of the Domestic sector. The coefficients are within the limits of stationarity indicating the residual series is white noise. In addition, the Ljung-Box Q statistic [Brockwell and Davis, 2002] for lags $h = 20$ gives a Q value of 23.38. This is lower than the critical chi-square of 31.41 at the 95% probability level suggesting that the residuals produced by the ARIMA(0,1,0) model for the Non-Domestic sector are not significant. Thus, the ARIMA(0,1,0) model is proposed for the Non-Domestic electricity consumption in the United Kingdom.

9.5.3 Total Electricity Consumption

The ARIMA modelling of the Total electricity consumption is very similar to that for the Non-Domestic sector of the United Kingdom. The original Total electricity consumption data are not stationary with ACF and PACF plots very similar to those of the Non-Domestic sector. The differenced data showed stationarity with ACF and PACF plots similar to those shown in Figure 9.10. The best model selected using the AICC criteria is the ARIMA(0,1,0) model. The maximum likelihood estimate of the model, after adjusting for the mean and differencing is

$$Y_t = 5.11 + Y_{t-1} + e_t \tag{9.6}$$

where, e_t is approximated by a zero mean white noise (WN) sequence, i.e. $e_t \sim$ WN(0, 36.65). The ARIMA(0,1,0) has given a good fit of the historical data with very low MAPE value as shown in Figure 9.13. The ACF and PACF of the residuals produced are shown in Figure 9.14. The correlation coefficients are well within the limits of stationarity. This means that the residuals can be regarded as white noise. In addition, the Ljung-Box Q statistic [Brockwell and Davis, 2002] for lags $h = 20$ gives a Q value of 13.17. The corresponding critical chi-square of 31.41 at the 95% probability level further suggests that the residuals produced by the ARIMA(0,1,0) model for the Total electricity consumption are white noise. Thus, the ARIMA(0,1,0) model is accepted for forecasting the Total electricity consumption in the United Kingdom.

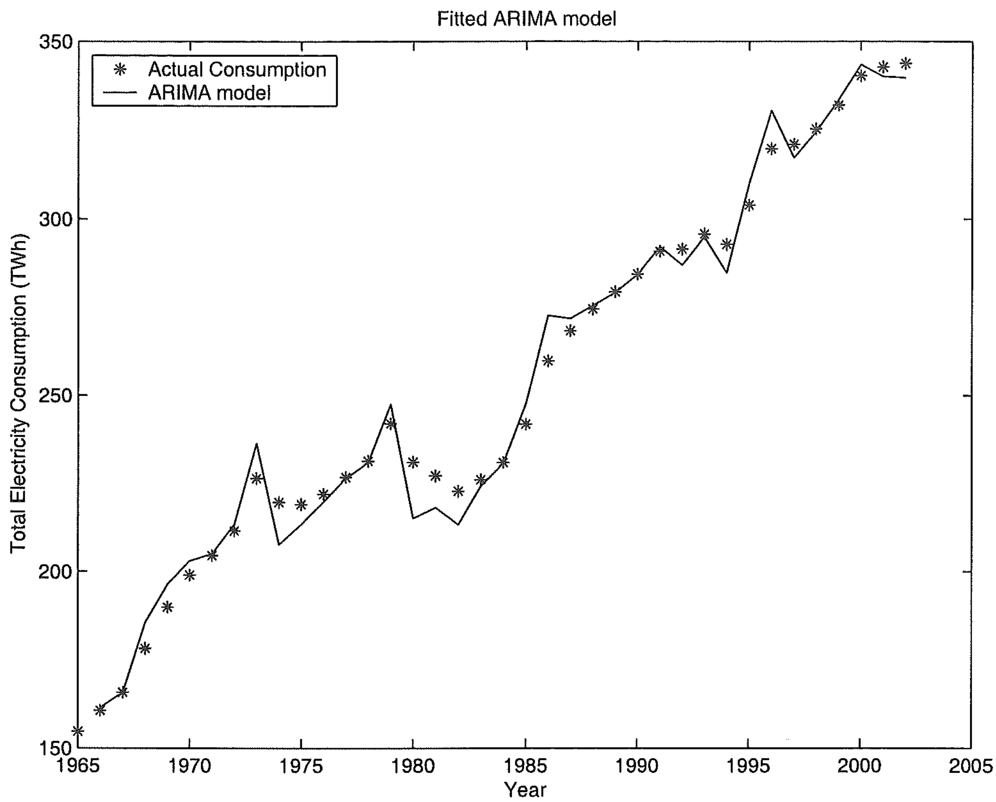

Figure 9.13 Fitted ARIMA model for the Total electricity consumption (MAPE = 1.82)

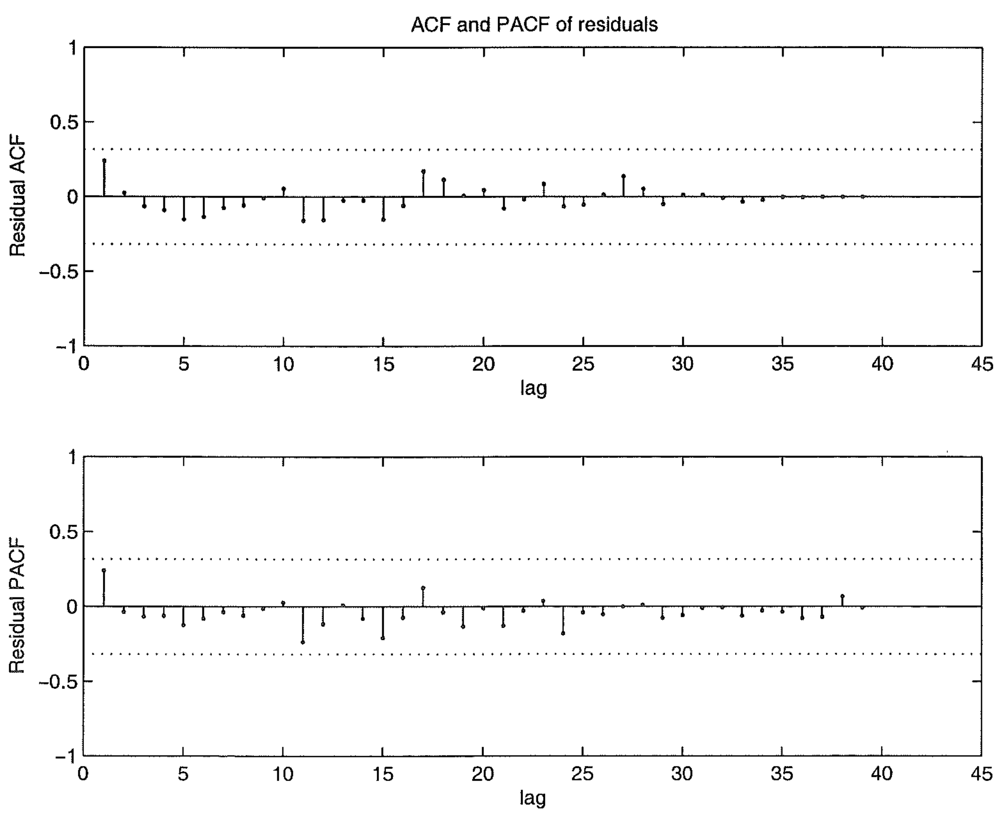

Figure 9.14 ACF and PACF of the residuals given by the Total consumption model for the UK

9.6 HARVEY LOGISTIC AND HARVEY MODELS

The Harvey Logistic and Harvey models are applied to the electricity consumption data in the United Kingdom as for the other countries. The resulting models for the Domestic, the Non-Domestic and the Total electricity consumption of the United Kingdom are:

Harvey Logistic models:

Domestic: $$\ln y_t = 2\ln Y_{t-1} + 91.9 - 0.051t \tag{9.7}$$

Non-Domestic: $$\ln y_t = 2\ln Y_{t-1} + 98.3 - 0.054t \tag{9.8}$$

Total: $$\ln y_t = 2\ln Y_{t-1} + 105.4 - 0.058t \tag{9.9}$$

Harvey models:

Domestic: $$\ln y_t = 0.222\ln Y_{t-1} + 51.33 + 0.0261t \tag{9.10}$$

Non-Domestic: $$\ln y_t = -2.18\ln Y_{t-1} - 66.29 + 0.0397t \tag{9.11}$$

Total: $$\ln y_t = -2.60\ln Y_{t-1} - 45.21 + 0.0308t \tag{9.12}$$

In both cases, t is the time in years from 1965.

Figure 9.15 shows the fitted Harvey Logistic models while Figure 9.16 shows the fitted Harvey models for electricity consumption in the United Kingdom. Table 9.3 shows the MAPE and DW values for all the sectors. Both the models have given very good fits of the historical data with similar MAPE values. However, the Harvey models have given slightly better fits than the Harvey Logistic models. The DW values are also close to 2 indicating that the errors produced by all the developed models are white noise.

Table 9.3 MAPE value for the fitted Harvey Logistic and Harvey models for the UK

	MAPE			DW		
Model	Domestic	Non-Domestic	Total	Domestic	Non-Domestic	Total
Harvey	2.42	2.23	1.80	1.5	1.8	1.5
Harvey Logistic	2.29	2.21	1.79	1.4	1.8	1.5

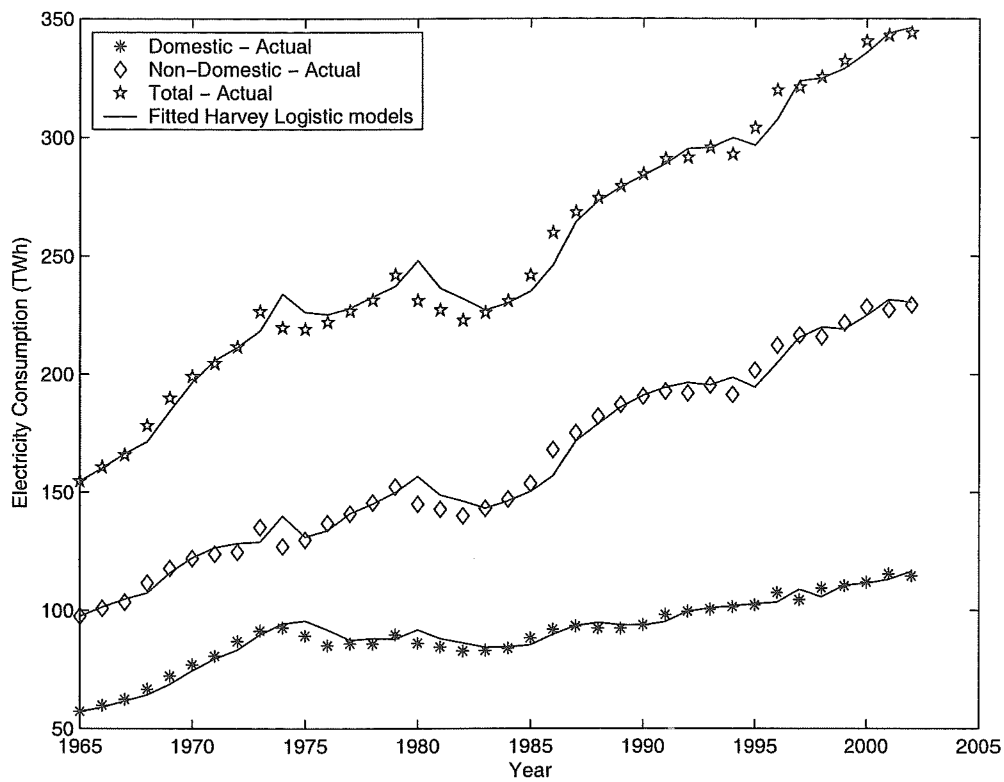

Figure 9.15 Fitted Harvey Logistic models for the UK

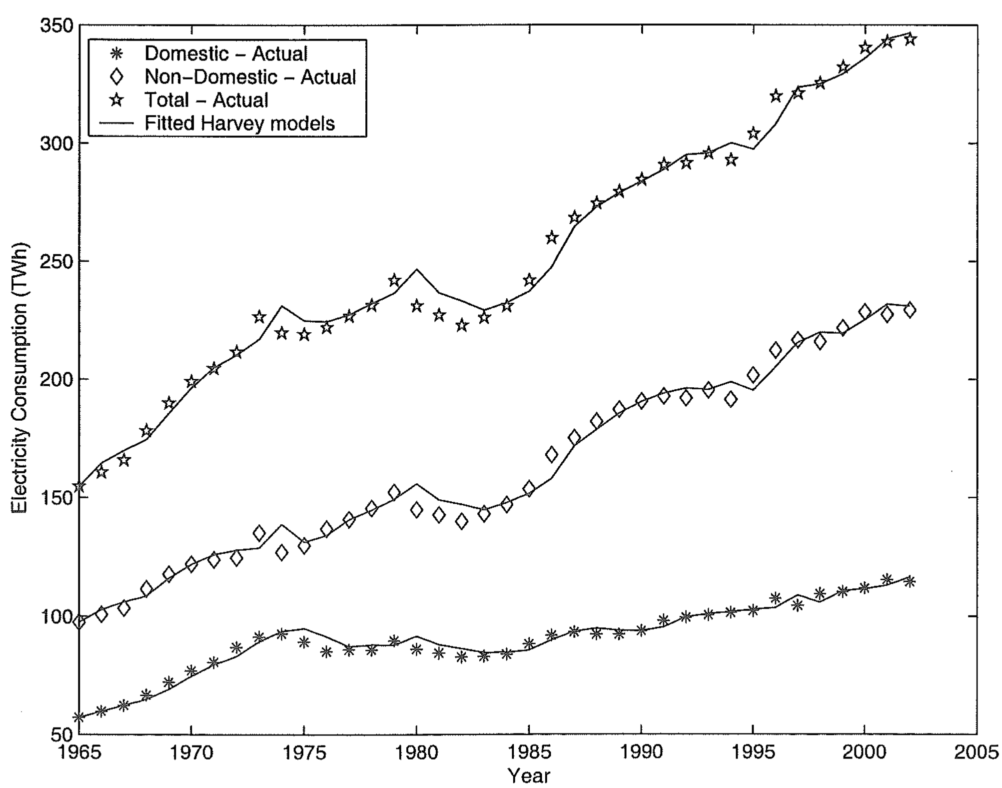

Figure 9.16 Fitted Harvey models for the UK

9.7 THE VAL MODEL

9.7.1 Estimation and Re-estimation of Saturation Levels

The VAL model uses GDP and population to re-estimate the saturation levels. These data are only available from 1970 to 2002. Therefore, the electricity consumption data from 1970-2002 are also used in the calculation of the asymptotes by the Fibonacci search technique. The Fibonacci search technique is applied over a period of 13 years from 1990-2002. That is, asymptotes are calculated for each of the periods 1970-1990, 1970-1991,.....,1970-2002 giving the asymptotes for 1990, 1991,...., 2002 respectively. Figure 9.17 shows the asymptotes obtained by the Fibonacci search technique.

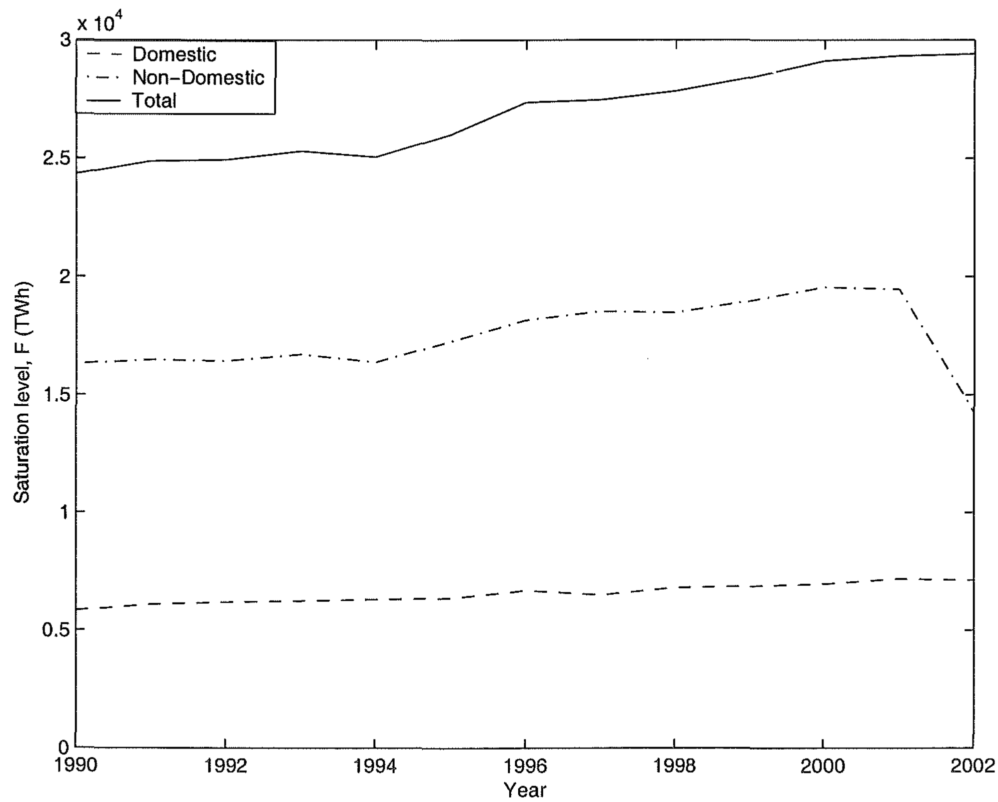

Figure 9.17 Saturation levels obtained by Fibonacci search technique for the UK

The asymptotes are increasing over the years, except for 2002 of the Non-Domestic sector. Although there is a similar growth pattern in electricity consumption in the Non-Domestic sector and the Total electricity consumption, the sudden drop in the saturation level as compared to the Total electricity consumption reflects some immaturity in the

Non-Domestic sector. This indicates that the Non-Domestic sector may not have gone beyond the early stages of growth for a stable Fibonacci search technique to be applied.

Table 9.4 shows the correlation between the explaining variables, GDP and population, and the saturation levels of electricity consumption by the Fibonacci search technique. The correlation between the explaining variables and the Domestic and the Total electricity consumptions are high enough for them to be used in re-estimating the saturation levels by a multiple linear regression technique. However, the correlation between the explaining variables and the Non-Domestic sector are too low to be used in the re-estimation process. Although this is an initial sign towards the elimination of the Non-Domestic sector model, it will be retained at this stage to test for the ability of the explaining variables to re-estimate the saturation levels.

Table 9.4 Correlation between the explaining variables and saturation levels

Saturation	Explaining variables	
	GDP	Population
Domestic	0.959	0.968
Non-Domestic	0.388	0.255
Total	0.980	0.964

The estimated saturation levels for the Domestic, the Non-Domestic and the Total electricity consumption of the United Kingdom are re-estimated by a multiple linear regression technique using the GDP and population of the United Kingdom. Figures 9.18 to 9.20 show the re-estimated saturation level for the VAL model along with the saturation levels obtained by the Fibonacci search technique for the Domestic, the Non-Domestic sectors and the Total electricity consumption respectively. The Domestic and the Total consumption saturation levels are re-estimated by the VAL model far better than that for the Non-Domestic saturation levels. The low correlations in the Non-Domestic sector along with the immaturity in the Non-Domestic sector have led to the inaccurate re-estimates in the Non-Domestic sector.

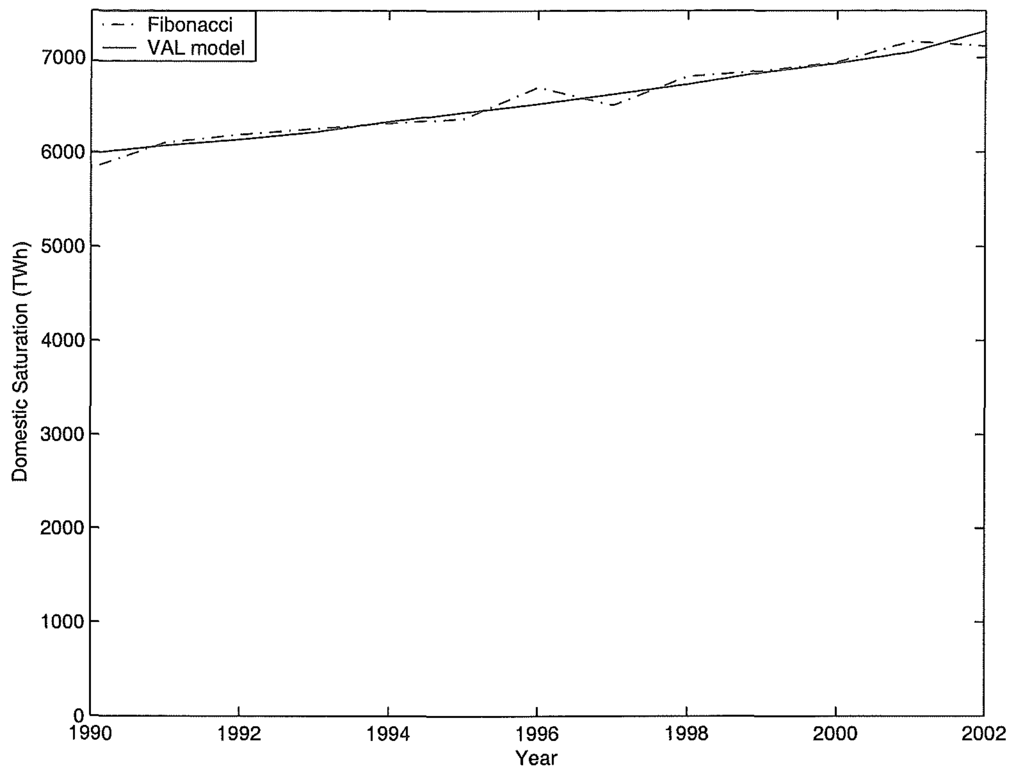

Figure 9.18 Estimated Domestic saturation levels by the VAL model

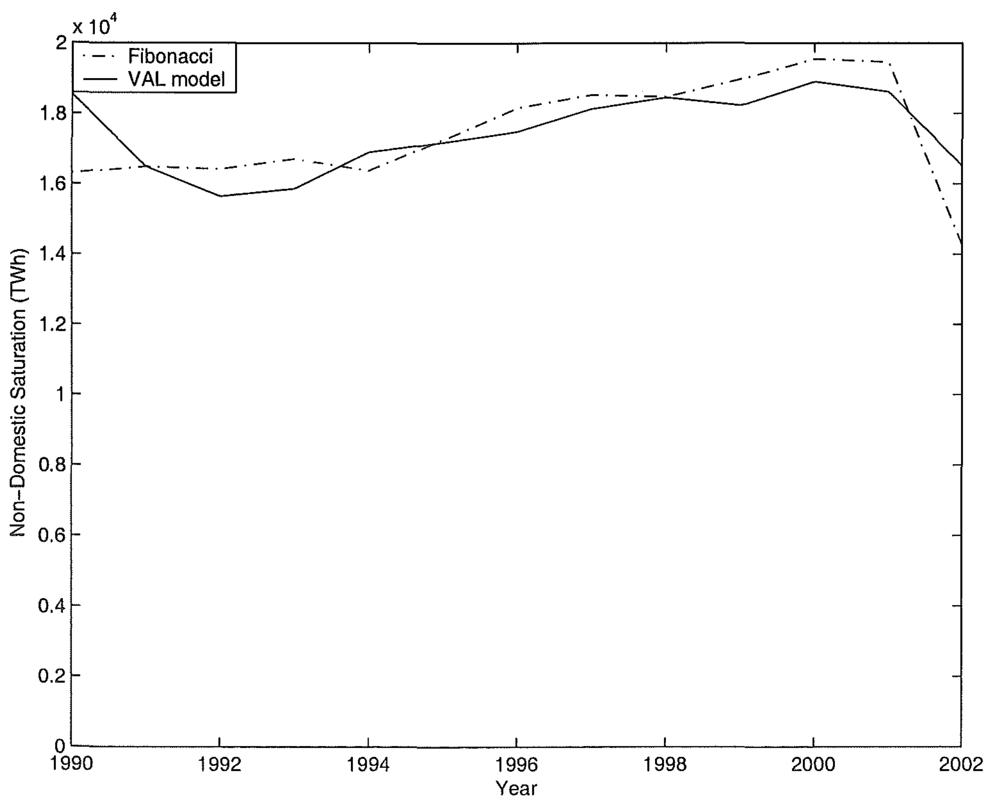

Figure 9.19 Estimated Non-Domestic saturation levels by the VAL model

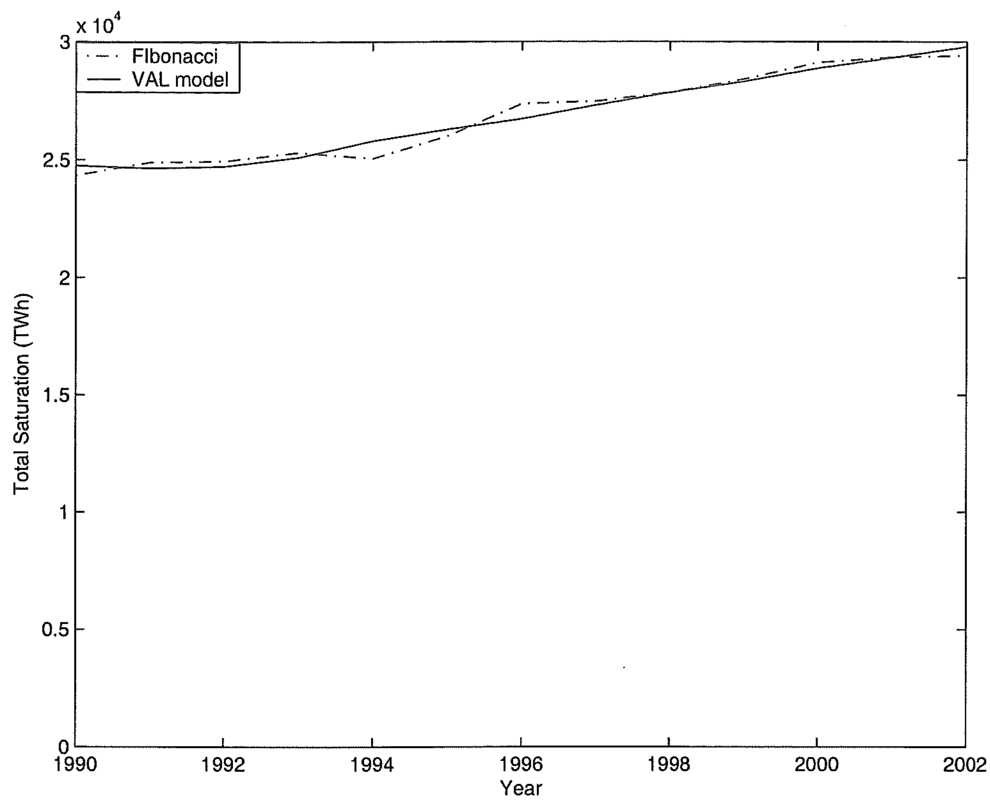

Figure 9.20 Estimated Total consumption saturation levels by the VAL model

Table 9.5 summarises the test results of the Durbin-Watson (DW) statistic, coefficient of determination r^2 and F test [Makridakis *et al.*, 1998] for this process. The DW values in the Domestic and the Total electricity consumption saturation are much closer to 2 than that for the Non-Domestic sector. The coefficient of determination is too low for the Non-Domestic sector while it has failed the F-test. These poor results along with the low correlation values observed previously in Table 9.4 excluded the VAL model from being applied to the Non-Domestic sector of the United Kingdom. Thus, the VAL models are only proposed for the Domestic and the Total electricity consumption.

Table 9.5 Statistical test results for re-estimation of saturation levels

	DW	r^2	F	critical F
Domestic	2.5	0.94	79.1	7.2
Non-Domestic	1.3	0.51	5.3	7.2
Total	1.8	0.96	126.2	7.2

9.7.2 Developed VAL Models

Based on the previous analysis, the proposed VAL model for the Domestic sector is

$$f_D = \frac{F_D(X)}{1+\exp(-24.6+0.0102t)} \tag{9.13}$$

And that for the Total electricity consumption is

$$f_T = \frac{F_T(X)}{1+\exp(-39.1+0.0173t)} \tag{9.14}$$

where, the variable saturation levels $F_D(X)$ and $F_T(X)$ are estimated using GDP (X_1) and population (X_2) and are as follows.

$$F_D(X) = -2.41\times10^4 + 1.51X_1 + 0.508X_2 \tag{9.15}$$

$$F_T(X) = -1.20\times10^4 + 21.0X_1 + 0.400X_2 \tag{9.16}$$

The GDP and population are forecasted using ARIMA techniques. These forecasted values are used in obtaining future saturation values. The asymptote obtained for each of the years to be forecasted is then used in Equation 9.13 and 9.14 to obtain the VAL model forecasts.

9.7.3 Comparison with the Logistic Model

Figure 9.21 shows the forecasting accuracy of the Logistic model compared with the VAL model for a period of nine years from 1994 to 2002. The VAL model has given much better MAPE values than the Logistic model for the Domestic sector. The VAL model has also given better forecasts in the Total consumption except for the first three years. Although the Logistic model can be applied for the period 1965-2002, for this comparison the Logistic model is applied for the period 1970-2002 as the VAL model is applied for the same period. This issue will be discussed further when comparing the forecasting accuracy of all the models.

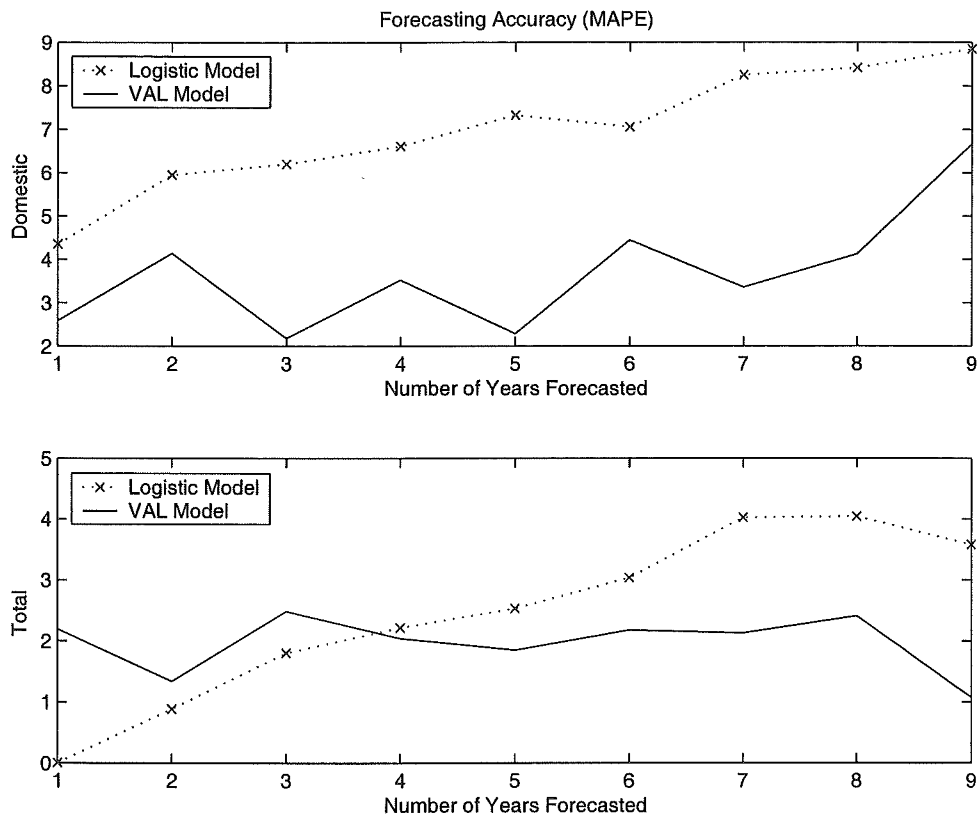

Figure 9.21 Forecasting accuracy of the Logistic model with VAL model

9.8 COMPARISON OF THE MODELS

9.8.1 Comparison of Model Fit and Forecasting Accuracy

Forecasting accuracies of all the models developed for the United Kingdom are compared using MAPE. The Logistic model, the Harvey Logistic model, the Harvey model and the ARIMA model make use of all available electricity consumption data from 1965 onwards. However, the Combined model and the VAL model uses the electricity consumption, GDP and population data from 1970 as the GDP and population are available from 1970 onwards. The actual data of the forecasted period is held out in each case for calculating the MAPE. The MAPE values are calculated from 1 year ahead forecasts to 9 years ahead forecasts. Figure 9.22 shows the forecasting accuracy of all the models for the Domestic, the Non-Domestic and the Total electricity consumption for the United Kingdom. Note that there is no VAL model for the Non-Domestic sector as explained in Section 9.7.1.

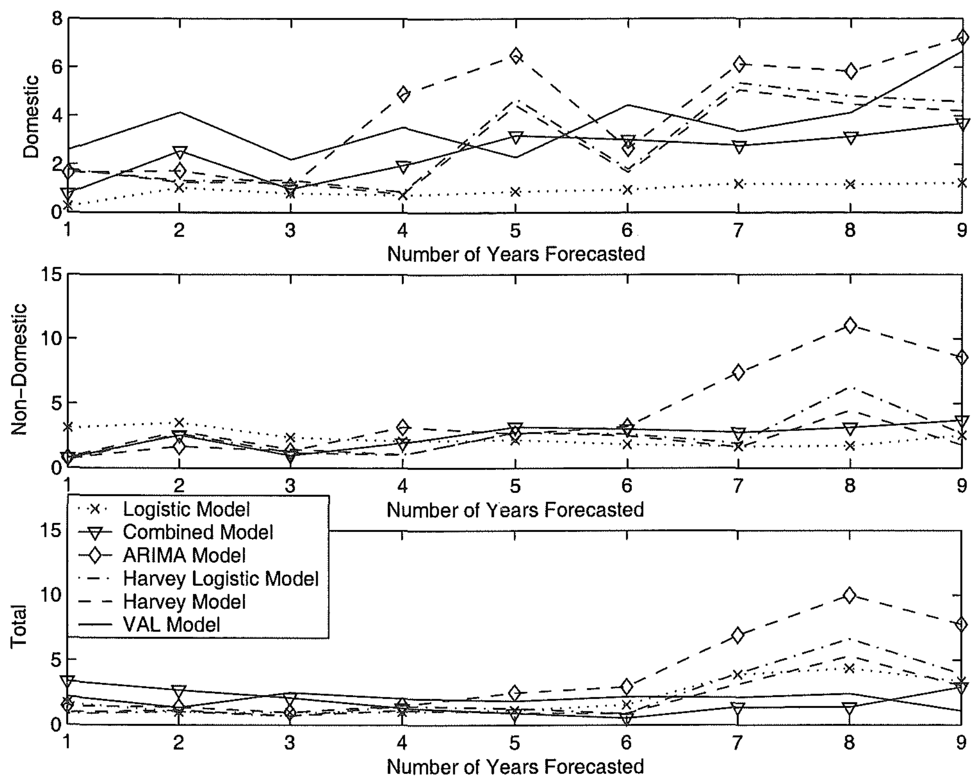

Figure 9.22 Forecasting accuracies of all models for the UK

The forecasting accuracies given by most models are very similar especially for the Non-Domestic and the Total electricity consumption. To compare the forecasting accuracy, the nine year period is divided into short term (1-3 years), medium term (4-6 years) and long term (7-9 years) forecasts. Table 9.6 shows the rankings of the models for forecasting accuracies and model fit to the historical data.

For the Domestic sector, the Logistic model has given the best forecasts for the short, medium and long term. The Harvey model gave the second best short and medium term forecasts and the third best long term forecasts next to the Combined model. The short term forecasts given by the Combined model, ARIMA model and Harvey model are also very similar to the Harvey model which is ranked the second best. Overall, the worst forecasts in the Domestic sector are given by the ARIMA model. However, it has given the best model fit of the historical data. The best overall forecasts are given by the Logistic model followed by the Combined model and the Harvey model.

Table 9.6 Model rankings for the United Kingdom (1 = best, 6 = worst)

Model	Domestic					Non-Domestic					Total				
		Forecast accuracy					Forecast accuracy					Forecast accuracy			
	fit	Short	medium	long	**Overall**	fit	Short	medium	long	**Overall**	fit	Short	medium	long	**Overall**
Logistic	5	1	1	1	**1**	5	4	1	2	**2**	5	3	4	4	**4**
Combined	3	3	4	2	**2**	1	5	4	1	**4**	1	6	1	2	**1**
ARIMA	1	5	6	6	**6**	4	1	5	5	**5**	4	4	6	6	**6**
Harvey Logistic	4	4	3	5	**4**	3	2	3	4	**3**	3	1	3	5	**5**
Harvey	2	2	2	3	**3**	2	3	2	3	**1**	2	2	2	3	**2**
VAL	6	6	5	4	**5**	6	n/a	n/a	n/a	**n/a**	6	5	5	1	**3**

In the Non-Domestic sector, the best forecasts are given by the ARIMA model for the short term, Logistic model for the medium term and Combined model for the long term. However, the best overall forecasts are given by the Harvey model due to its consistent low MAPE values over the entire period. The worst overall forecasts are once again given by the ARIMA model. The Logistic model gave the second best Non-Domestic forecasts. Although the Combined model gave the best model fit, very close fits are also given by the ARIMA, Harvey Logistic and Harvey models.

In the Total consumption, the best short and medium term forecasts are given by the Harvey models while the VAL model gave the best long term forecasts just ahead of the Combined model. The best model fit is again given by the Combined model. The ARIMA model is again ranked as the worst model for the Total electricity consumption. The Combined model gave the best overall forecasts while the Harvey model followed very closely with the second best overall forecasts.

One important difference can be observed when Figure 9.21 is compared with Figure 9.22. In Figure 9.21, the best forecasts are generally given by the VAL model. However, in Figure 9.22 the Domestic forecasts of the Logistic models are far better than the VAL model while close forecasts are given for the Total consumption. In Figure 9.21 the forecasts of the Logistic model are obtained using electricity consumption data from 1970 to 2002 while those for Figure 9.22 are obtained using data from 1965 to 2002. It is clear that the use of this extra data in the latter has significantly improved the Logistic model forecasts. However, attempt to include these extra data in the VAL model failed to give statistically acceptable VAL models for the same period. As both these models heavily rely on the asymptotes obtained, the use of these extra data had different impacts on the two models. As observed previously in Figure 9.1, the non-uniformity in the electricity consumption pattern has a great impact on the saturation level calculated. This suggests that the VAL model is very unsuitable to be applied to the electricity consumption of the United Kingdom. However, the results may be improved using more historical data.

In all cases, the ARIMA model gave the worst overall forecasts. In general, the Logistic model, Harvey model and Combined model are the best models for electricity consumption forecasting in the United Kingdom.

9.8.2 Comparison of Forecasts

Figures 9.23 to 9.25 show the forecasts from 2003 to 2017 for the six developed models for electricity consumption in the United Kingdom. For the Domestic sector, the Combined model and the VAL model gave very high forecasts. The Logistic model and the ARIMA model gave very similar medium level forecasts while the Harvey Logistic and the Harvey model gave very similar low forecasts. For the Non-Domestic sector, very similar medium level forecasts were given by the Combined model, the Harvey model and the ARIMA model. The Logistic model gave the highest forecasts while the Harvey Logistic model gave the lowest forecasts. For the Total consumption, very high forecasts were given by the VAL model while the other models gave relatively close forecasts.

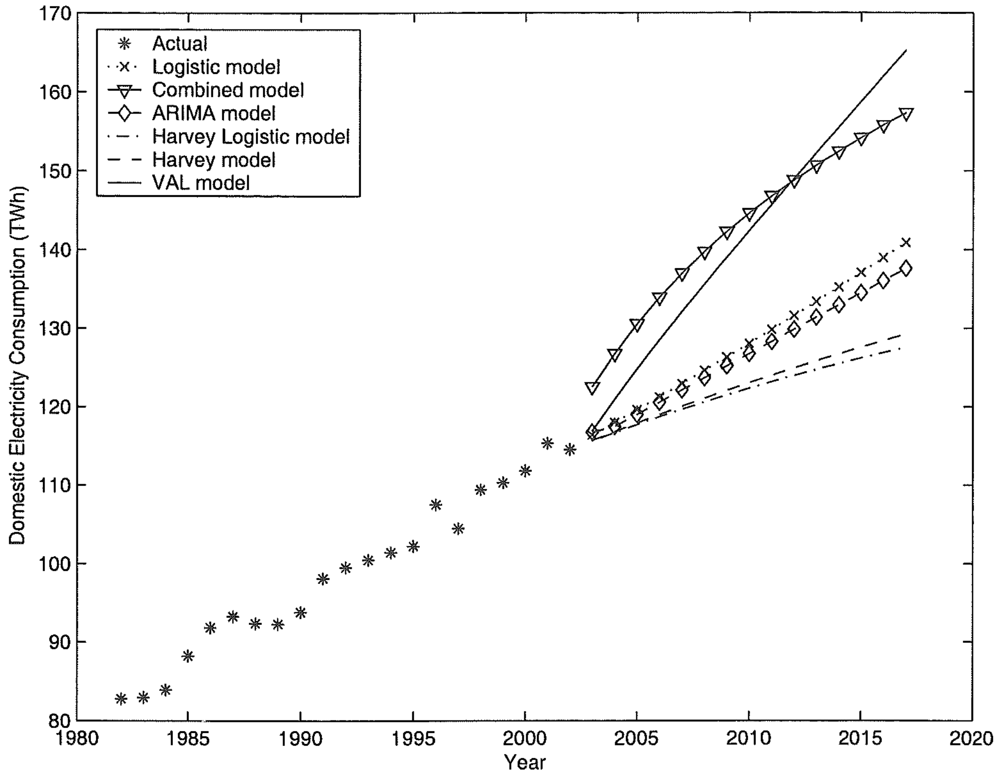

Figure 9.23 Comparison of the Domestic forecasts by all the developed models for the UK

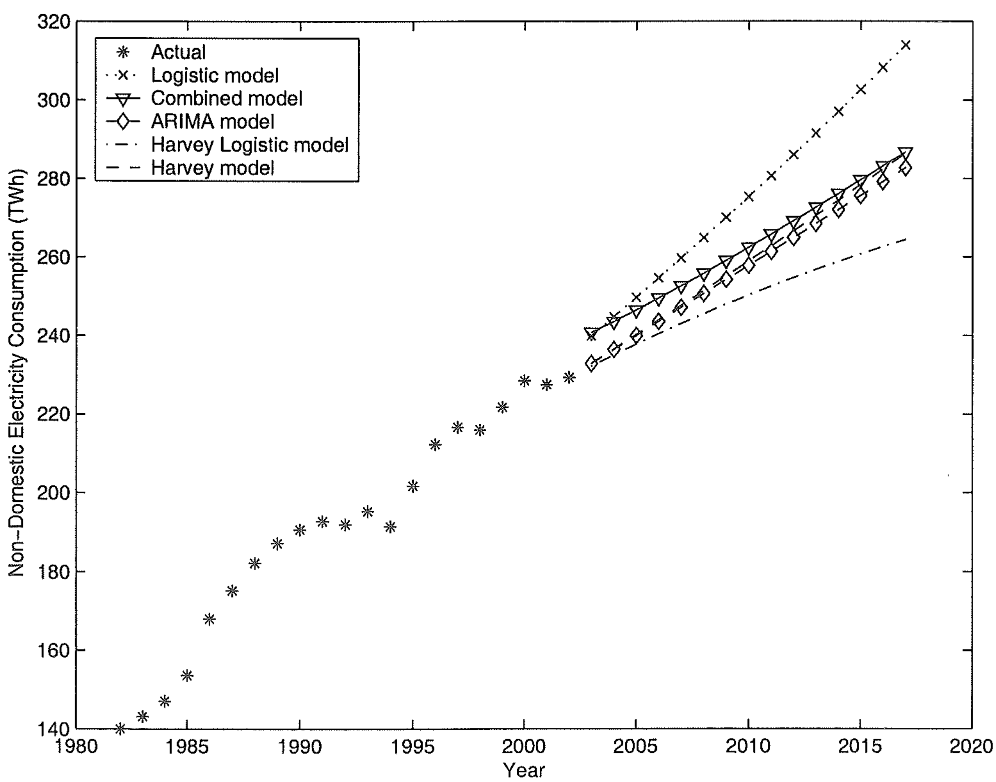

Figure 9.24 Comparison of the Non-Domestic forecasts by all the developed models for the UK

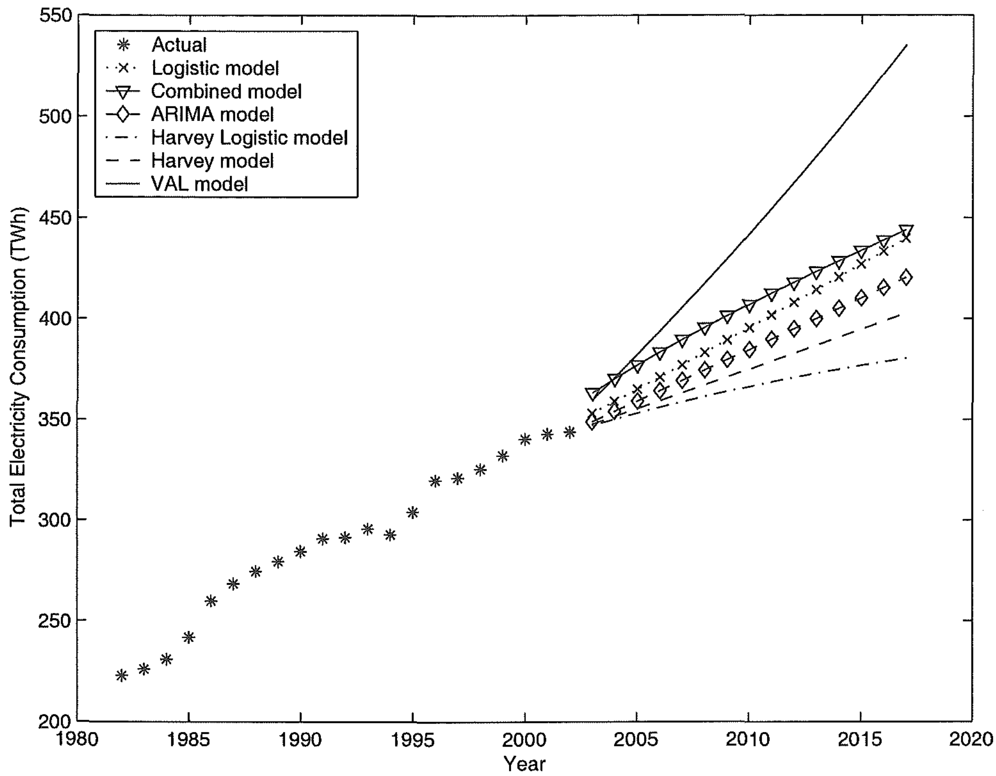

Figure 9.25 Comparison of the Total consumption forecasts by all the models for the UK

The Total electricity consumption forecasts given by the developed models for the United Kingdom are compared with the Energy Information Administration (EIA) [EIA_2, 2003] forecasts for the years 2005, 2010 and 2015. Table 9.7 summarises the forecasts. The ARIMA model forecasts are within 1% to the EIA projections for all the years compared. While the Logistic model forecasts are within 4% to the EIA forecasts, the forecasts by the Harvey model and the overall best Combined model are approximately within 5% of the EIA forecasts. The VAL model forecasts are the furthest from the EIA projections. The ARIMA model, which gave the worst forecasting accuracy, has given the closest forecast to the EIA projections. A similar observation like this was also noted in the comparison of the forecasts of the developed models for the United States in Chapter 8, again suggesting that the EIA model uses a technique very similar to those used by the ARIMA models.

Table 9.7 Comparison of EIA projections with the developed models for Total electricity consumption of the United Kingdom (% Difference to the EIA projections)

Model	2005		2010		2015	
	TWh	*% Difference*	*TWh*	*% Difference*	*TWh*	*% Difference*
EIA	358	_	387	_	414	_
Logistic	365	1.92	396	2.27	427	3.04
Combined	377	5.04	407	4.91	433	4.39
ARIMA	359	0.28	385	-0.52	410	-0.98
Harvey Logistic	353	-1.42	359	-7.80	377	-9.81
Harvey	356	-0.56	375	-3.20	395	-4.81
VAL	382	6.28	442	12.44	507	18.34

9.9 SUMMARY

In this chapter, a brief overview of the electricity industry in the United Kingdom has been described. The six proposed forecasting models have been applied to the electricity consumption in the United Kingdom. All models except the VAL model generally gave acceptable fits to the historical electricity consumption data. The Combined model and VAL model used GDP and the population of the United Kingdom as explaining variables.

Comparison of the forecasting accuracy revealed that the Logistic model, Harvey model and the Combined model are in general the best models for the United Kingdom. Although the Logistic model for the United Kingdom gave poor model fit to the historical data, their forecasting accuracies are very close to the Harvey and Combined models. It was found that the ARIMA model which gave the worst forecasting accuracy among the six developed models gave the closest forecasts to the Energy Information Administration (EIA) forecasts [EIA_2, 2003]. The ARIMA forecasts were within 1% to the EIA forecasts for the years 2005, 2010 and 2015 while the next closest forecasts given by the Logistic model, the Harvey model and the Combined models were within 4%, 5% and 6% respectively.

Chapter 10

WORLD ELECTRICITY CONSUMPTION FORECASTS

10.1 INTRODUCTION

World electricity consumption is growing at a faster rate than the world energy consumption. According to Energy Information Administration (EIA) forecasts [EIA_1, 2004], world electricity consumption is projected to nearly double by 2025 while the world energy consumption is expected to grow by 54 percent. This indicates the strong demand for electricity worldwide. Coal is the dominant fuel in the world's electricity markets and in almost any region power generation accounts for most of the projected growth in coal consumption [EIA_1, 2004]. This is even more significant for countries with the largest coal reserves. For example, the United States with the largest share of the world's recoverable coal reserves, along with China, India, Germany, Poland, South Africa, and Australia all with substantial reserves of coal, generate more than half of the total electricity produced using coal [EIA_1, 2004].

Electricity generation from natural gas is a popular choice for many countries. The consumption of natural gas fired electricity has increased by an average of about 6.9% per year from 1970 to 2001 [EIA_1, 2004]. The use of combined-cycle gas turbines, that are usually cheaper to construct and more efficient than other fossil fuel generation, is increasing in industrialised nations. In addition, the fact that natural gas is seen as a much cleaner fuel than other fossil fuels is increasing the drive for natural gas in electricity generation.

Currently, 19 countries depend on nuclear power for at least 20% of their electricity generation [International Atomic Energy Agency, 2004]. Nuclear power is a relatively expensive source of electricity generation when compared with coal or natural gas. In addition, concerns about plant safety, radioactive waste disposal, and proliferation of nuclear weapons have led to strong public sentiment against nuclear power generation in many parts of the world [EIA_1, 2004]. However, improvements in operating and safety performance of nuclear power have improved its image and future global prospects. By the end of January 2004, there were 440 nuclear power plants in operation worldwide and another 31 nuclear power plants were under construction [International Atomic Energy Agency, 2004].

Renewable energy resources account for about 20% of the world electricity generation [EIA_1, 2004]. In the industrialised countries renewable energy accounts for 18% of the electricity generated while in the developing countries renewable energy accounts for 24%. The fastest growth of renewable energy in the recent years is shown by wind power [EIA_1, 2004].

In this chapter, annual electricity consumption of the world [EIA_2, 2004] from 1980 to 2002 are divided into geographical regions and the proposed electricity forecasting models developed and applied to New Zealand, the Maldives, the United States and the United Kingdom are applied and analysed for these regions of the world. The models have also been applied to the world total electricity consumption data. This study will give an overall picture of the performances of these models with the different patterns of electricity consumption growth in the world's regions.

10.2 WORLD ELECTRICITY CONSUMPTION

The world electricity consumption data [EIA_2, 2004] is divided into six basic country groupings as used by the EIA [EIA_1, 2004] [EIA_2, 2004]. Details of the data are given in Appendix B. This allows for an easy comparison of the regional forecasts of the developed models with those of the EIA projections [EIA_2, 2003]. The six basic country groupings and the countries in each region are as follows [EIA_1, 2004]:

- *Industrialised Countries* – This contains 15 percent of the 2004 world population. This group is further divided into 3 groups. They are:
    1. *North America* - United States, Canada, and Mexico.
    2. *Western Europe* - Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.
    3. *Industrialised Asia* - Japan, Australia, and New Zealand.

- *Eastern Europe and the Former Soviet Union (EE/FSU)* contain 6 percent of the 2004 world population. The countries in the Eastern Europe (EE) are Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Hungary, Macedonia, Poland, Romania, Slovakia, Slovenia, and Yugoslavia. The countries in the Former Soviet Union (FSU) are Armenia, Azerbaijan, Belarus, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, Russia, Tajikistan, Turkmenistan, Ukraine, and Uzbekistan.

- *Developing Asia* contains 54 percent of the 2004 world population. They are Afghanistan, Bangladesh, Bhutan, Brunei, Cambodia (Kampuchea), China, Fiji, French Polynesia, Guam, Hong Kong, India, Indonesia, Kiribati, Laos, Malaysia, Macau, Maldives, Mongolia, Myanmar (Burma), Nauru, Nepal, New Caledonia, Niue, North Korea, Pakistan, Papua New Guinea, Philippines, Samoa, Singapore, Solomon Islands, South Korea, Sri Lanka, Taiwan, Thailand, Tonga, Vanuatu, and Vietnam.

- *Middle East* contains 4 percent of the 2004 world population. The countries in this region are Bahrain, Cyprus, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syria, Turkey, the United Arab Emirates, and Yemen.

- *Africa* contains 14 percent of the 2004 world population. The countries in Africa are Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Congo (Brazzaville), Congo (Kinshasa), Djibouti, Egypt, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Ivory Coast, Kenya, Lesotho, Liberia, Libya, Madagascar, Malawi, Mali, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Reunion, Rwanda, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, St. Helena, Sudan, Swaziland, Tanzania, Togo, Tunisia, Uganda, Western Sahara, Zambia, and Zimbabwe.

- *Central and South America* contains 7 percent of the 2004 world population. The countries are Antarctica, Antigua and Barbuda, Argentina, Aruba, Bahama Islands, Barbados, Belize, Bolivia, Brazil, British Virgin Islands, Cayman Islands, Chile, Colombia, Costa Rica, Cuba, Dominica, Dominican Republic, Ecuador, El Salvador, Falkland Islands, French Guiana, Grenada, Guadeloupe, Guatemala, Guyana, Haiti, Honduras, Jamaica, Martinique, Montserrat, Netherlands Antilles, Nicaragua, Panama Republic, Paraguay, Peru, Puerto Rico, St. Kitts-Nevis, St. Lucia, St. Vincent/Grenadines, Suriname, Trinidad and Tobago, Turks and Caicos Islands, Uruguay, U.S. Virgin Islands, and Venezuela.

A total of eight effective regions including the three sub-regions in the industrialised world along with the other five regions in the developing world are used in building the models. A ninth group that contains the world total electricity consumption which sums the totals of all the regions is also used. Figures 10.1 and 10.2 show the electricity consumption in the eight regions and world total respectively from 1980 to 2002. North America consumes the highest amount of electricity throughout the period and by 2002 this region consumed about 30% of the world electricity consumption. Developing Asia shows the highest rate of growth and by 2002 this region was the second highest electricity consumer. Eastern Europe and the Former Soviet Union show recovery from the economic and social declines of the early 1990s due to the slow or declining population in this region associated with the fall of the Soviet regime. Africa and the Middle East consumed the smallest amount of electricity. Although the Middle East represents 4% of the world population, the low electricity consumption in Africa with 14% of the world population indicates the low level of electrification in some countries of this region. In general, the electricity consumption in the industrialised countries is increasing at a slower rate than those in the developing world. The electricity sectors in the industrialised world are well established and the development of more efficient equipment slows down the rate of growth.

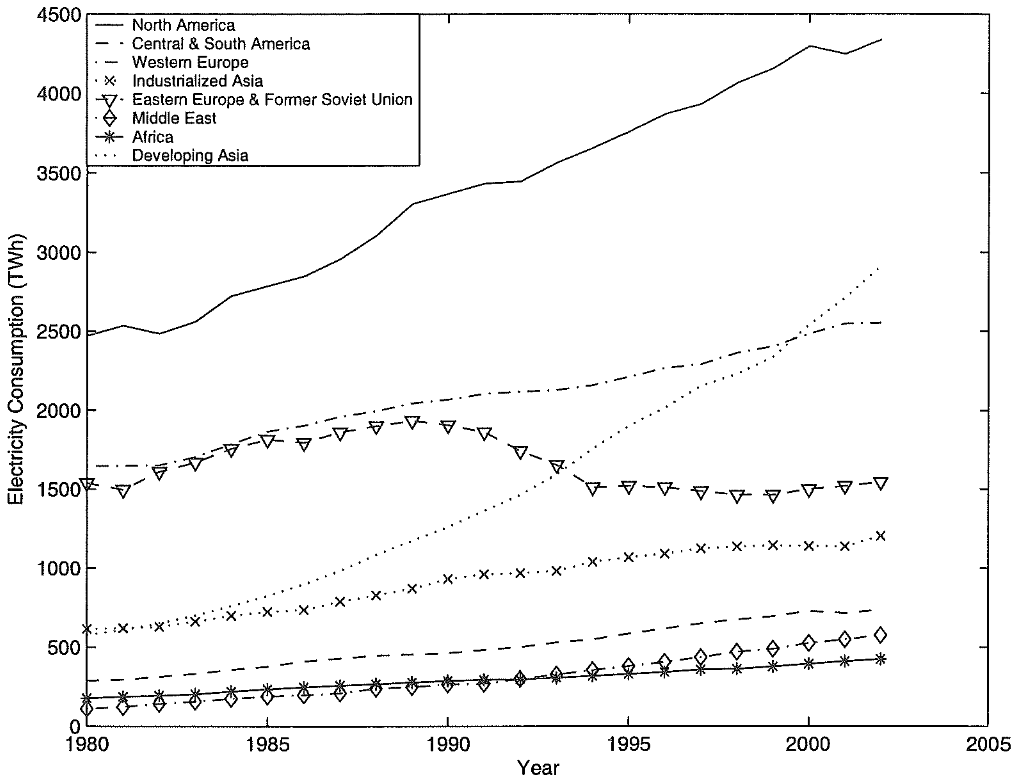

Figure 10.1 Electricity consumption in the world (8 regions)

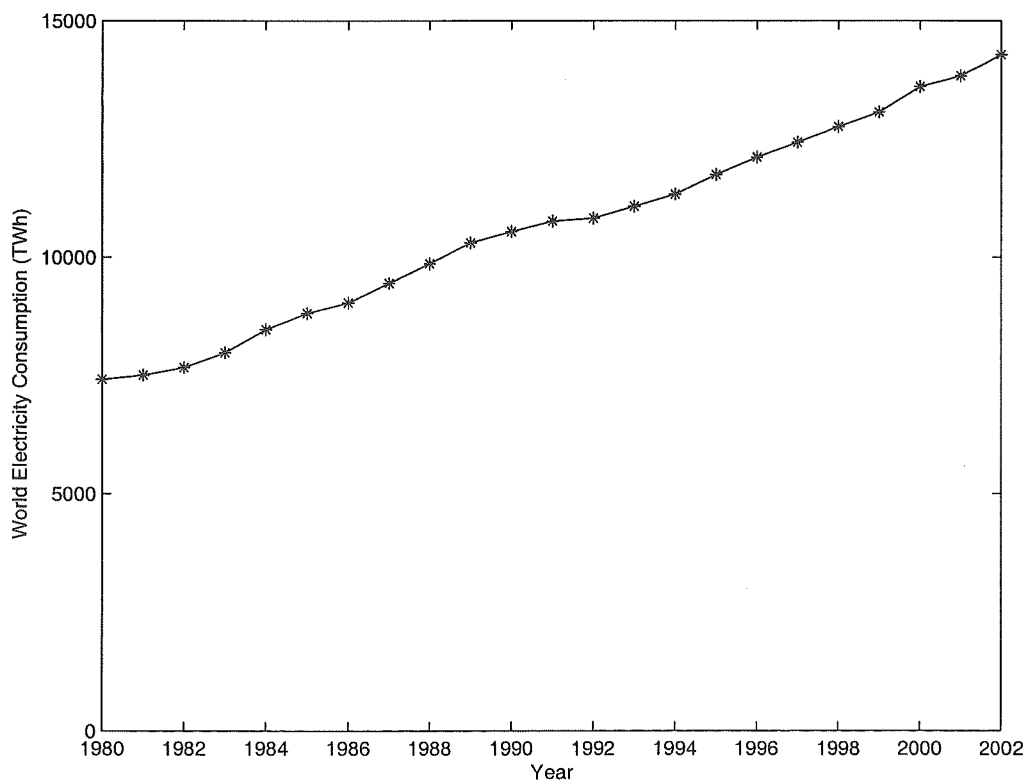

Figure 10.2 World total electricity consumption from 1980 to 2002

The world total electricity consumption is increasing over the whole period. It nearly doubled in 20 years.

10.3 APPLICATION OF THE MODELS

The Logistic model, Harvey Logistic model, Harvey model, Combined model, ARIMA model and VAL model are applied to the electricity consumption data of North America, Central and South America, Western Europe, Industrialised Asia, Eastern Europe and the Former Soviet Union, Middle East, Africa and Developing Asia, and to the world total electricity consumption. None of the model fits to the historical data for the regions have been presented in this chapter as they essentially all produce curves similar to those in Figure 10.1 and 10.2, except in certain circumstances explained in the sections to follow. For each of the models, their model fits to the world total electricity consumption are presented.

10.3.1 Logistic and Harvey Logistic Models

The three growth curve models, Logistic, Harvey Logistic and Harvey, are applied to each of the 9 data sets. The model fit is calculated using mean absolute percentage error (MAPE) [Makridakis *et al.*, 1998]. The Durbin-Watson (DW) Statistic is used to test the adequacy of the model fit to the historical data [Makridakis *et al.*, 1998]. Table 10.1 summarises the model fit and the DW statistics for the eight regions and the world total electricity consumption. All the models have given generally low MAPE values except for the Eastern Europe and the Former Soviet Union. Although the fit of the Harvey Logistic and Harvey models are better than the Logistic model for the Eastern Europe and the Former Soviet Union they are still worse than those for all other regions. The sudden drop in the electricity consumption in the Eastern Europe and the Former Soviet Union due to the fall of the Soviet regime cannot be matched by the continuous Logistic growth curve. The discrete form models, Harvey Logistic and Harvey, have resulted in better fits and hence lower MAPE values. Generally, the Harvey model has given the best fit of the historical data and the Logistic model has given the worst fit to the historical data in all regions.

Table 10.1 MAPE and DW values for world electricity consumption

Region	MAPE			DW		
	Logisitic	Har_Log	Harvey	Logistic	Har_Log	Harvey
North America	1.49	1.30	1.22	1.08	2.04	1.66
Central and South America	2.22	1.61	1.52	0.69	1.90	1.70
Western Europe	1.51	1.08	1.06	0.51	1.10	1.09
Industrialized Asia	2.18	1.85	1.81	0.84	1.27	1.36
Eastern Europe and FSU	7.37	2.91	3.02	0.18	0.90	0.85
Middle East	2.29	2.38	2.01	1.00	1.91	1.90
Africa	2.17	1.18	1.09	0.39	1.26	1.43
Developing Asia	1.55	1.35	1.13	0.82	1.23	1.42
World total	1.28	0.96	0.87	0.58	1.42	1.41

In the analysis of the errors created by the model fits, the DW values for the Logistic model generally indicate positive autocorrelation in the errors produced. However, in the Harvey Logistic and Harvey models most of the DW values are closer to the desired value of 2 indicating that the errors produced by these models are white noise. However, Eastern Europe and the Former Soviet Union, and Western Europe show significant correlations for these models.

Figure 10.3 shows the model fits given by the Logistic, Harvey Logistic and Harvey models for the total electricity consumption of the world. Generally all the three models have given very close fit to the historical data with average errors of 1.28% for the Logistic model, 0.96% for the Harvey Logistic model and 0.87% for the Harvey model. As the MAPE values suggest, the best model fit is given by the Harvey model.

10.3.2 Combined Models

The Combined models are obtained using population and gross domestic product (GDP) of the respective regions [EIA_2, 2004]. Appendix B gives the details of these data. The population accounts for the total population of all countries within a particular region. Similarly, the GDP accounts for the total of the individual GDPs of all countries in billions of 1995 United States dollars. The GDP series for some countries are not available and therefore are not included in the total GDP figures for the regions[1]. However, the contribution to GDP by these countries would be very small and thus could not make much change to the overall value of GDP in the respective regions.

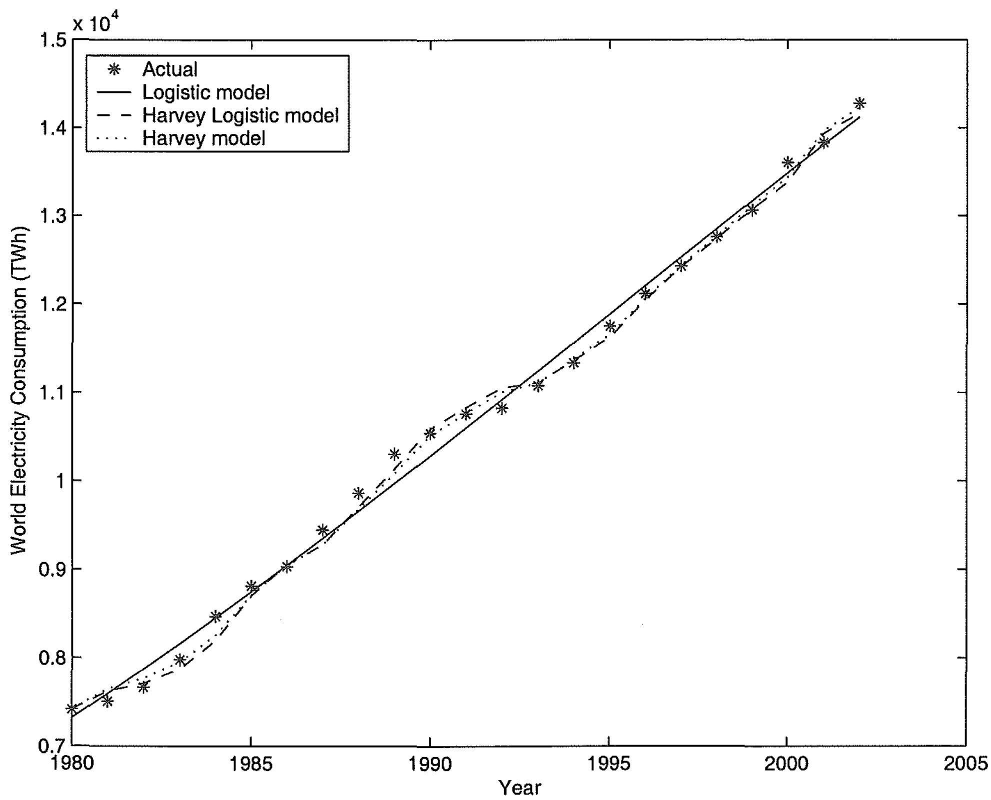

Figure 10.3 Fitted Logistic, Harvey Logistic and Harvey models for the world total electricity consumption

The GDP and population are correlated with the corresponding electricity consumption and the developed models for each region are tested using the adjusted coefficient of determination r^2, F-test and t-tests [Makridakis *et al.*, 1998]. Table 10.2 shows the

[1] The GDP series is not used for the following countries. Central and South America – Antarctica, Falkland Islands, French Guiana, Guadeloupe, Martinique, Montserrat, Turks and Caicos Islands, Virgin Islands U.S. and Virgin Islands British. Middle East – Yemen. Africa – Liberia, Reunion, Saint Helena, Sao Tome and Principe and Western Sahara. Developing Asia - French Polynesia, Guam, Kiribati, Nauru, New Caledonia and Niue Tonga.

correlations and the results of these tests for all the regions and the world total electricity consumption. The table also lists the model fit to the historical data in terms of MAPE. The correlation between electricity consumption and the corresponding GDP and population for all regions and the world total, except those for Eastern Europe and the Former Soviet Union, are high, indicating that a suitable Combined model using these variables could be developed for each of those regions. In the case of Eastern Europe and the Former Soviet Union, the sudden change in the electricity consumption and the resulting effects on GDP and population due to the fall of the Soviet regime has resulted in low correlation values. However, since the same two variables are used for all other 7 regions and the world total, the model for this region will be accepted if it could satisfy the required F-test and t-tests. The 99% critical F-value and t-values are 5.78 and 2.52 respectively for all regions. The absolute values of the F-tests and t-tests are much higher than these for all regions suggesting to accept the developed Combined models. For Eastern Europe and the Former Soviet Union, the F value and t value are lower than those for the other regions. However, these values are still higher than the critical values even at the 99% confidence level. Therefore, this model has also been accepted for further comparison.

Table 10.2 Statistical tests and fitting of the Combined models for the world data

Region	Correlation with		Adjusted	F-test	t-test		Fitting
	GDP	Population	r^2		t_1	t_2	(MAPE)
North America	0.990	0.992	0.969	695	13.4	24.9	1.82
Central and South America	0.990	0.993	0.982	1202	21.4	29.1	2.54
Western Europe	0.991	0.975	0.969	686	53.6	-15.8	1.41
Industrialized Asia	0.993	0.990	0.972	764	26.7	13.5	2.17
Eastern Europe and FSU	-0.595	0.033	0.507	29	-10.9	7.9	4.38
Middle East	0.987	0.984	0.959	522	19.4	13.9	5.75
Africa	0.971	0.994	0.979	1022	7.4	39.1	2.33
Developing Asia	0.999	0.984	0.996	5086	112.1	-8.9	1.15
World total	0.997	0.996	0.988	1804	33.5	28.1	1.33

The Combined models have also given very low MAPE values. Apart from the high MAPE values for Eastern Europe and the Former Soviet Union and the Middle East, these models have given rise to comparable fits of the historical data when compared with the growth curve models presented in Section 10.3.1. The fit given by the Combined model for the world total electricity consumption is shown is Figure 10.4. The model has given a very good fit of historical data with a MAPE of just 1.33%.

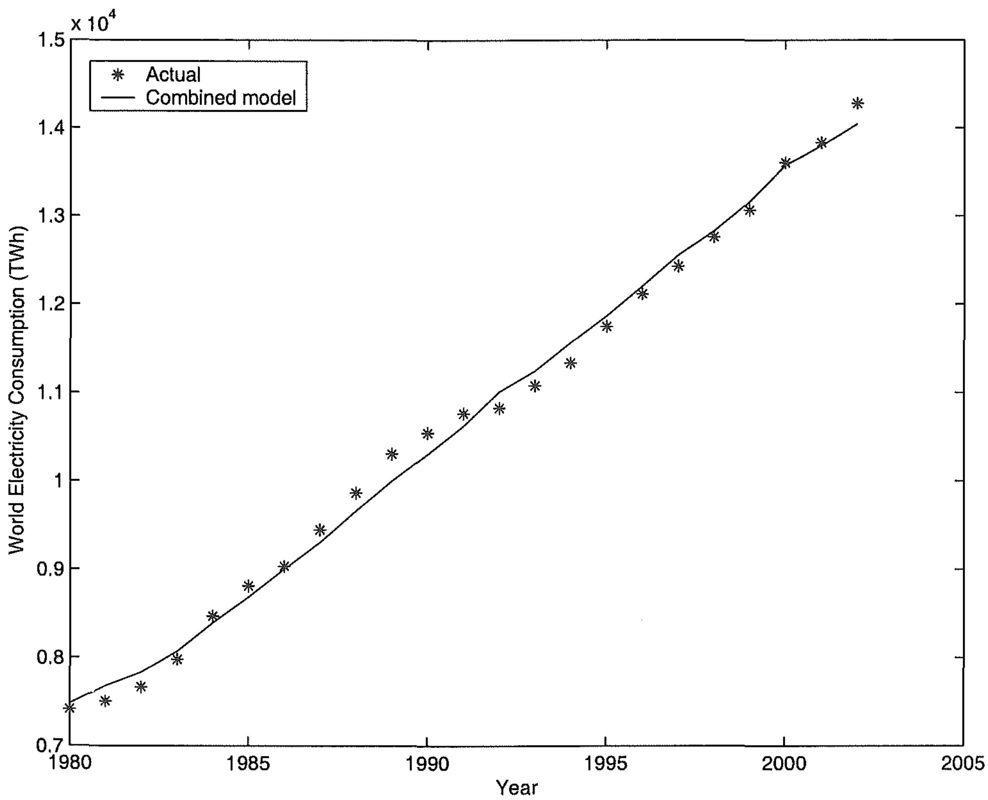

Figure 10.4 Combined model fit for the world total electricity consumption

10.3.3 ARIMA Models

When using the ARIMA model, each of the electricity consumption data sets for the regions and the world total is tested independently for stationarity, identification, estimation and diagnostic checking of residuals [Makridakis *et al.*, 1998]. The plots of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) are used in observing the stationarity of the data [Makridakis *et al.*, 1998]. A bias corrected version of Akaike's Information Criterion (AIC) known as AICC [Brockwell and Davis, 2002] is used in selecting the best model for each of the data sets. The selected models are those with the lowest AICC values. The software package ITSM2000 [Brockwell and Davis, 2002] is used in estimating the ARIMA models. The residuals produced by these models are tested using the Ljung-Box Q statistic compared with the chi-square (χ^2) distribution [Brockwell and Davis, 2002]. The fitted ARIMA models, the results of the Ljung-Box Q statistic along with the corresponding chi-square values, and the MAPE values of the model fits to the historical data are given in Table 10.3.

Table 10.3 Statistical test results and model fits for the ARIMA models

Region	Fitted ARIMA	Q value	chi-square value	MAPE
North America	ARIMA(0,1,0)	18.23	28.87	1.34
Central and South America	ARIMA(0,1,0)	19.57	28.87	1.57
Western Europe	ARIMA(0,1,0)	24.15	28.87	1.03
Industrialized Asia	ARIMA(0,1,0)	12.28	28.87	1.83
Eastern Europe and FSU	ARIMA(1,2,0)	16.89	28.87	2.51
Middle East	ARIMA(0,2,1)	17.57	28.87	2.15
Africa	ARIMA(0,1,0)	16.82	28.87	1.13
Developing Asia	ARIMA(4,2,0)	9.47	28.87	0.77
World total	ARIMA(0,1,3)	20.78	28.87	0.63

For all the regions of the world and the world total electricity consumption data, the Q values obtained are lower than the critical chi-square values indicating that the residuals produced by all the developed models are not significant and can be regarded as white noise. In addition, the ACF and PACF of the residuals in each region indicated stationarity with the coefficients well within the required bounds for stationarity more than 95% of the time. The ACF and PACF plots of the residuals for the world total electricity consumption are shown in Figure 10.5. The coefficients are within the dotted bounds for stationarity. This further suggests that the residuals are white noise. The MAPE values of the fitted ARIMA models are also very low. Some of these ARIMA models have given rise to even lower MAPE values than those of the growth curve models presented in Table 10.1. Even in this case, the worst fit is given for Eastern Europe and the Former Soviet Union indicating the significance of the sudden changes in electricity consumption due to the fall of the Soviet regime in the early 1990s. The model fit given by the ARIMA model for the world total electricity consumption is shown in Figure 10.6. The ARIMA model has given a very close fit to the world electricity consumption data with a very low MAPE value of just 0.63%.

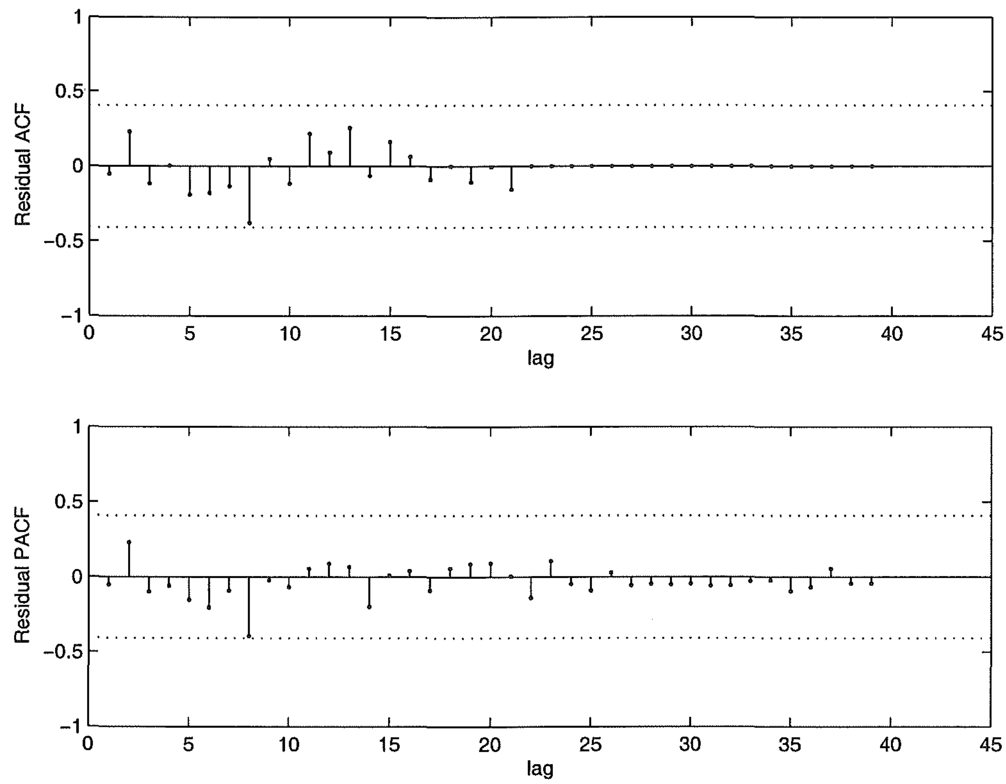

Figure 10.5 ACF and PACF of the residuals produced by the ARIMA model for the world total

10.3.4 Application of the VAL Model

The Fibonacci search technique is applied to the different regions and the world total electricity consumption data. The technique is applied to each of the data sets 1980-1993, 1981-1994, ..., 1980-2002 and the saturation level is obtained for each of the corresponding years 1993, 1994, ...,2002. The corresponding saturation levels obtained for each of these regions and the world total electricity consumption are shown in Figure 10.7.

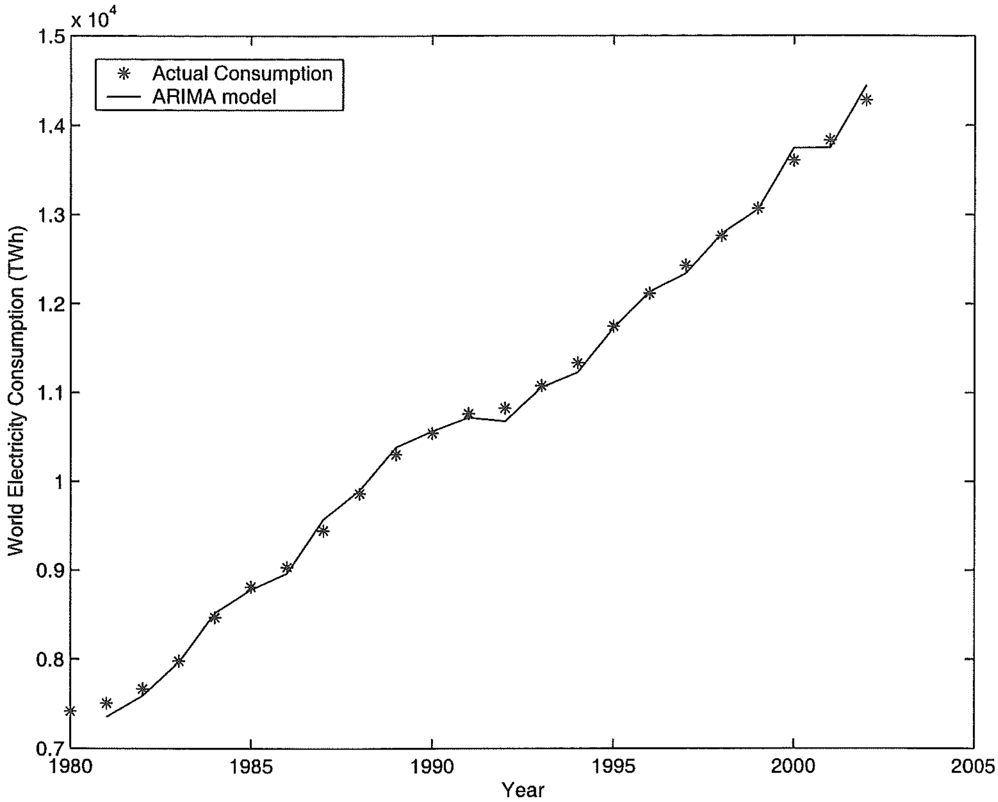

Figure 10.6 Fitted ARIMA model for the world total electricity consumption

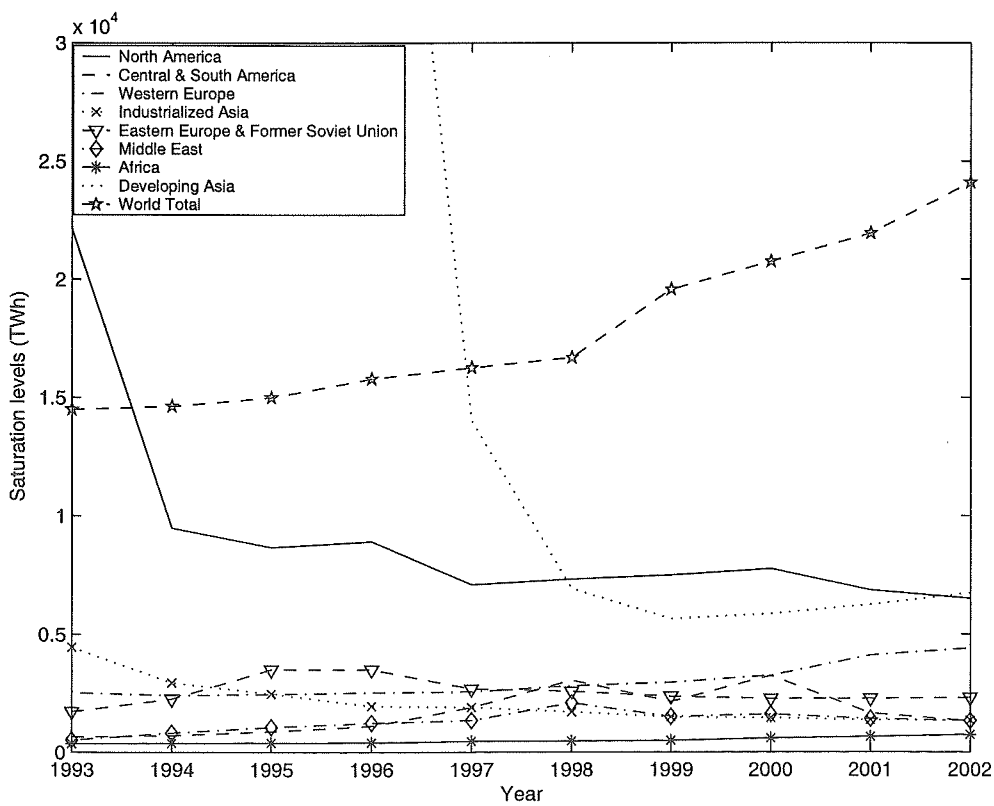

Figure 10.7 Saturation levels for all regions and world total

Developing Asia and North America gave very high saturation levels compared to the rest of the regions. The high saturation levels for North America are expected as this region has relatively higher levels of electricity consumption as compared to the other regions (Figure 10.1). However, both the Developing Asia and North America gave very unstable asymptotes especially during the initial years. The world total electricity consumption saturation levels appear mature with an increase in trend from 1993 to 2002. The behaviours of the other regions are not very apparent from Figure 10.7. Therefore, Figure 10.8 shows Figure 10.7 enlarged so that these regions can be more clearly observed.

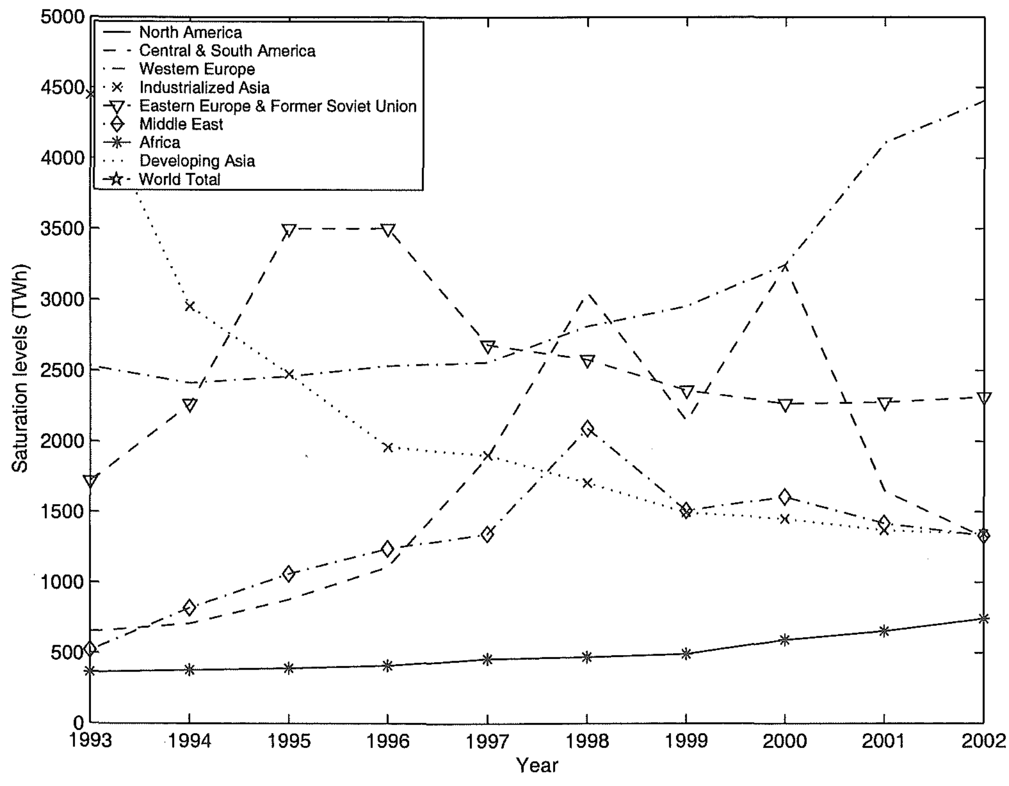

Figure 10.8 Figure 10.7 enlarged to show the unclear regions

The asymptotic levels for most of these regions are changing unexpectedly throughout the period. The unstable saturation levels for most of the regions indicate that the number of data points used in this analysis is not enough for the Fibonacci search technique to be applied effectively. This is an early indication that the VAL model may not be effectively applied to these data sets. Despite this, the VAL model has been applied to these data sets. The VAL models are statistically tested to determine how well the explaining variables GDP and population of each of these regions re-estimated the saturation levels, and how well the VAL model ultimately estimated the corresponding electricity consumption data. Table 10.4 shows the result of these tests.

Table 10.4 Statistical test results for estimation of saturation levels and electricity consumption by the VAL model

	Correlation with		r^2	*F*-test		
	GDP	Population		Saturation	Consumption	99% critical
North America	-0.65	-0.62	0.44	2.75	3.11	8.65
Central and South America	0.73	0.57	0.68	7.46	4.25	8.65
Western Europe	0.88	0.83	0.83	17.36	5.46	8.65
Industrialized Asia	-0.90	-0.89	0.82	15.69	3.48	8.65
Eastern Europe and FSU	-0.55	0.16	0.50	3.44	n/a	8.65
Middle East	0.73	0.67	0.60	5.35	5.65	8.65
Africa	0.96	0.95	0.92	40.99	11.13	8.65
Developing Asia	-0.64	-0.67	0.48	3.28	3.27	8.65
World total	0.95	0.96	0.91	37.55	11.18	8.65

When applied to most of the regions, the VAL models have given poor results. Apart from Western Europe, Africa and the World total, the correlation of the saturation levels with GDP and population is low. Thus, the resulting *F*-test results failed at the 99% probability level. The results of these *F*-tests are even lower or very close to the 95% critical value of 4.46. In the case of Africa and the World total where the saturation level *F*-tests are satisfied, the resulting consumption estimation *F*-tests are just satisfied at the 99% probability level.

Figure 10.9 shows the world electricity consumption as predicted by the VAL model and the Logistic model along with the actual electricity consumption data for the period 1993-2002. Clearly, the Logistic model has given rise to a much better fit to the historical data than those predicted by the VAL model. The VAL model can only be accepted for forecasting if it gives better forecasts than the Logistic model. The VAL model proposed for the world electricity consumption gave forecasts that are worse than the Logistic model. This suggests that the VAL model cannot be effectively applied to these data sets considered.

Previously, it was found that the VAL model could not be applied to the Non-Domestic sector data of New Zealand and the United Kingdom (See chapters 6 and 9). In the case of the Maldives (Chapter 7) it was also observed that the VAL model cannot be applied when too few data points are available. When the number of data points available are less the resulting growth in electricity consumption appear more immature and thus the asymptotes obtained by the Fibonacci search technique become unstable.

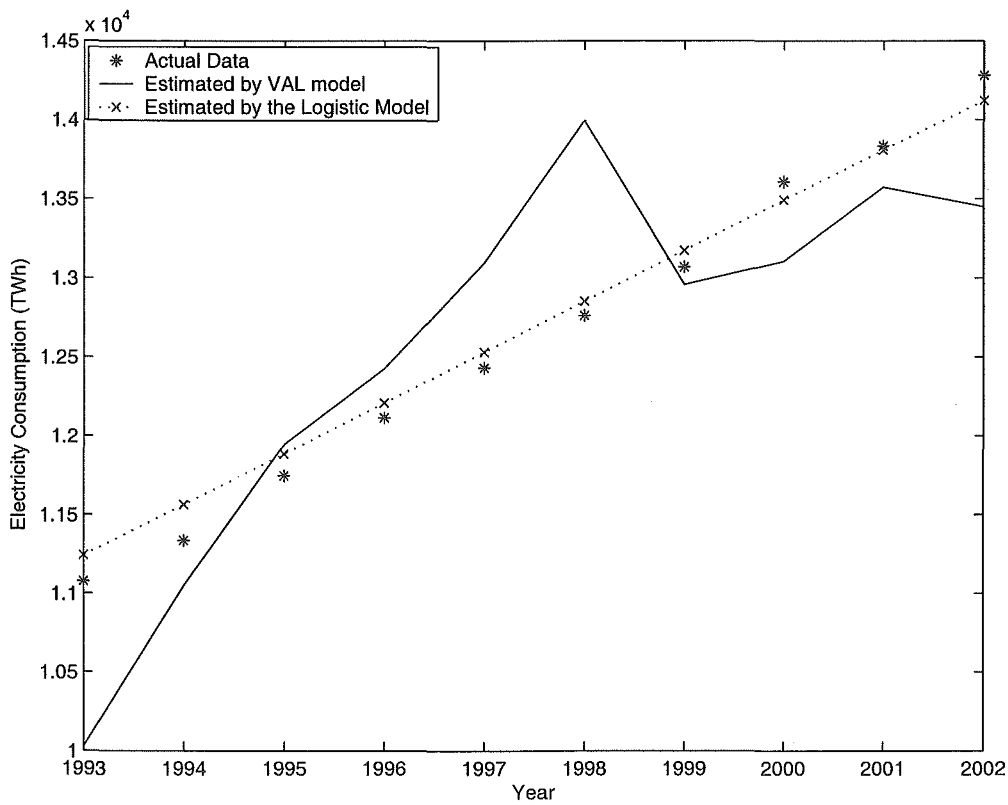

Figure 10.9 World electricity consumption estimated by the VAL model and the Logistic model

In the world total and regional electricity consumption, the data was available for 23 years from 1980 to 2002 [EIA_2, 2004]. In order to develop the VAL model for these data sets, saturation levels were initially estimated for 10 years from 1993 to 2002. That is, to obtain the saturation level at 1993 only 13 years of data from 1980 to 1993 can be used. These few data points could possibly be seen by the Fibonacci search technique as a market in the early phase of growth, although in reality it may be not. This leads to very high asymptotic levels. In addition, the number of data points available for correlation with GDP and population, and the resulting regression technique, is limited to 10 data points (from 1993 to 2003). This increases the instability in the regression technique [Farnum and Stanton, 1989]. Moreover, if the VAL model is to be used to compare the forecasting accuracy with the other models, discarding some data from the available 23 data points would lead to even more unstable asymptotes. Therefore, it was decided not to include the VAL model in applying and comparing the world total and regional electricity consumption. However, if more of the world total and regional data was available[2], the VAL model would give an effective model in forecasting world total and regional electricity consumption. The VAL model has been very effectively applied for the United States and New Zealand where more data points were available.

10.4 FORECASTING ACCURACY

The forecasting accuracies of all the developed models were measured from one year ahead through to nine years ahead using MAPE. In order to calculate the MAPE for the 9 years ahead forecasts, the actual electricity consumption data from 1994 - 2002 is held out while developing these models. The forecasts obtained by these models and the actual consumption data held out are then used to calculate the MAPE value.

Figure 10.10 shows the forecasting accuracies for these models for North America, Central and South America and Western Europe, while Figure 10.11 shows the forecasting accuracies for Industrialised Asia, Eastern Europe and the Former Soviet union and Middle East. Figure 10.12 shows the forecasting accuracies for Africa, Developing Asia and world total electricity consumption. The developed models have generally given low acceptable errors over the period compared. The worst forecasts are

---

[2] The world energy data *Energy Statistics Database* from 1950-2001 is available for sale from the United Nations Statistics Division. Web page http://unstats.un.org/unsd/ (on 27 July 2004). However, this was not within the scope of this research as the proposed models have already been applied with more data points to other countries (Chapters 6 to 9). Energy related data are also available from the International Energy Agency, (web page http://www.iea.org/dbtw-wpd/bookshop/b.aspx?subject=statistics) .

in general given for Eastern Europe and the Former Soviet Union region, reflecting the inaccuracies caused by the sudden changes in electricity consumption due to the fall of the Soviet regime. All the models have given very low errors for North America. The slightly high error from all models for the 2 year ahead forecasts (forecast for 2001) is very significant for this region. In 2001, the electricity consumption is lower than 2000. This decrease in actual electricity consumption as opposed to the increasing trend predicted by the forecasting models, has resulted in high errors for this year. The models for Central and South America also show a slight increase in error for this year.

For most regions, the average errors increase as the number of years forecasted increases. Most models for the Developing Asia region indicate that the errors are changing more unpredictably than for the other regions. Generally, all models have given very low consistent forecasts for the world total electricity consumption. The most consistent and accurate forecasts are given by the Harvey model with an average error of just 0.87% throughout the whole period. Even the Logistic model which gave the worst overall forecasts gave an average error of 3.6%.

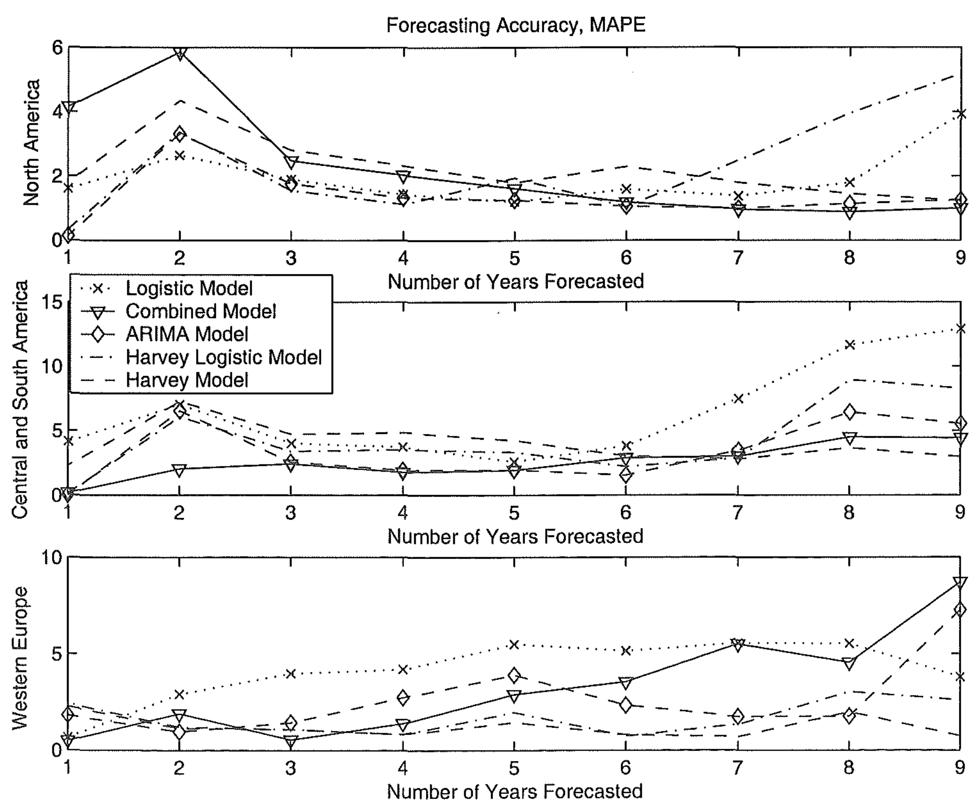

Figure 10.10 Accuracy plots for North America, Central & South America and Western Europe

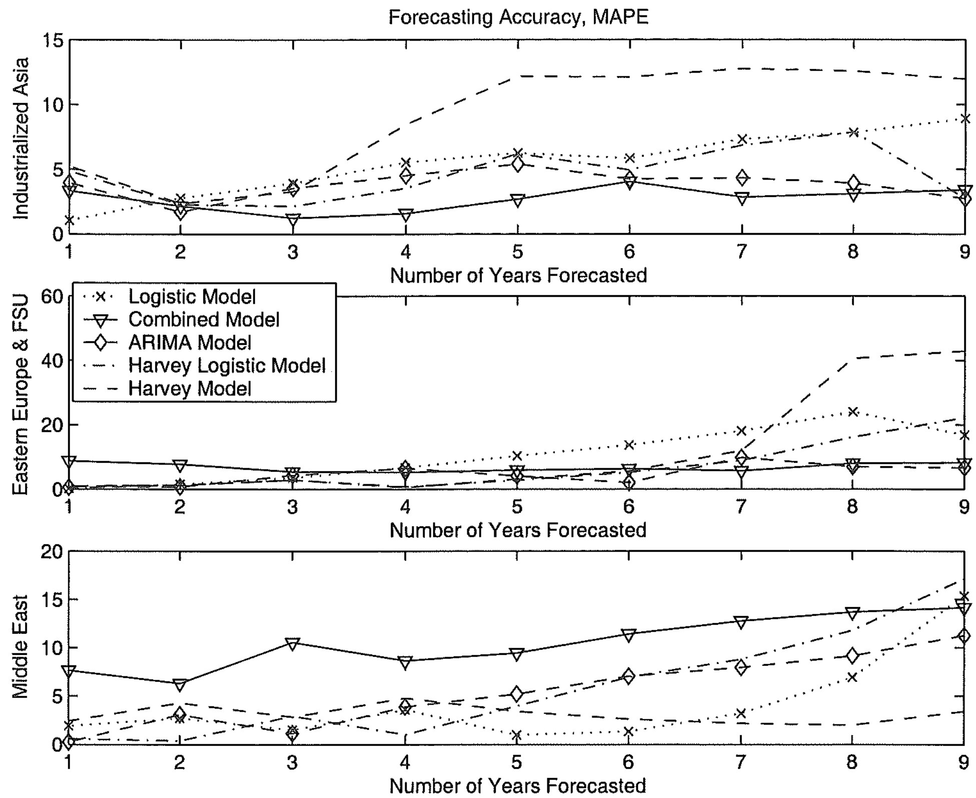

Figure 10.11 Accuracy plots for Industrialised Asia, Eastern Europe & the FSU and Middle East

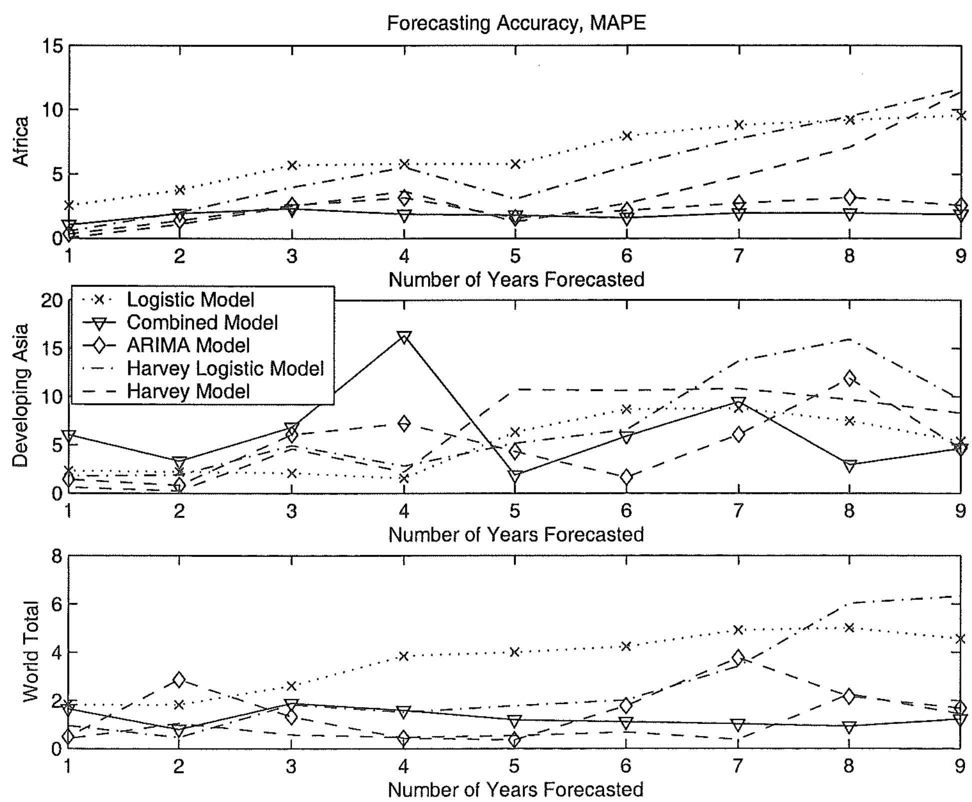

Figure 10.12 Accuracy plots for Africa, Developing Asia and world total electricity consumption

10.4.1 Model Rankings

The models are ranked according to the criteria of model fit, and short term (1 to 3 years), medium term (4 to 6 years) and long term (7 to 9 years) forecasting accuracies for all regions. Models are ranked from 1 (best) to 5 (worst) by taking the average of the MAPE values over the short, medium and long term. Models are ranked from the lowest MAPE (best model) to the highest MAPE (worst model). The overall rankings are calculated by taking the average of the MAPE values over the whole period compared. Table 10.5 summarises the ranking of the models for all regions and the world total electricity consumption.

For the industrialised countries of North America, the best short and medium term forecasts are given by the ARIMA model while the Combined model gave the best long term forecasts. The best overall forecasts were given by the ARIMA model. All the models in these regions gave reasonably low error values. While the best overall ARIMA model gave an error of 1.36%, the worst overall Harvey Logistic model gave an error of 2.32%.

For Central and South America, the Combined model gave the best short term forecasts, the ARIMA model gave the best medium term forecasts and the Harvey model gave the best long term forecasts. The Combined model gave the best overall forecast with an average error of 2.57%, while the Logistic model gave the worst overall forecasts with an error of 6.37%. All models gave more inaccurate forecasts for this region as compared to North America.

For the industrialised countries of the Western Europe, the Combined model gave the best short term forecast, while the Harvey model gave the best medium and long term forecasts. The Harvey model also gave the best overall forecasts for this region with an average error of just 1.22%. The worst overall forecasts for this region were again given by the Logistic model with an error of 4.14%.

For Industrialised Asia, the Combined model gave the best short, medium, long term and overall forecasts while the Harvey model gave the most inaccurate forecasts.

Table 10.5 Rankings of models for all regions (1 = best model and 5 = worst model)

Region	Term	Applied models				
		Logistic	Combined	ARIMA	Har_Log	Harvey
North America	short	3	5	1	2	4
	medium	3	4	1	2	5
	long	4	1	2	5	3
	overall	2	4	1	5	3
Central and South America	short	5	1	2	3	4
	medium	4	2	1	3	5
	long	5	2	3	4	1
	overall	5	1	2	4	3
Western Europe	short	4	1	2	4	3
	medium	5	3	4	2	1
	long	4	5	3	2	1
	overall	5	4	3	2	1
Industrialized Asia	short	2	1	3	4	5
	medium	4	1	2	3	5
	long	4	1	2	3	5
	overall	4	1	2	3	5
Eastern Europe and FSU	short	3	5	4	2	1
	medium	5	4	3	1	2
	long	4	1	2	3	5
	overall	4	3	1	2	5
Middle East	short	3	5	2	1	4
	medium	1	5	4	3	2
	long	2	5	3	4	1
	overall	2	5	3	4	1
Africa	short	5	3	2	4	1
	medium	5	1	2	4	3
	long	4	1	2	5	3
	overall	5	1	2	4	3
Developing Asia	short	2	5	3	4	1
	medium	3	5	1	2	4
	long	2	1	3	5	4
	overall	2	3	1	5	4
World total	short	5	3	4	2	1
	medium	5	3	2	4	1
	long	4	1	3	5	2
	overall	5	2	3	4	1

In Eastern Europe and the Former Soviet Union, the Harvey model gave the best short term forecast, the Harvey Logistic model gave the best medium term and the Combined model gave the best long term forecasts. Most models gave very accurate forecasts in the short to medium term although the ARIMA model gave the best overall forecasts. The Harvey model gave the worst overall forecasts for this region. The average errors by all models were the highest for this region due to the unpredictable pattern in electricity consumption in this region. The best overall model gave an average error of 4.6% while the worst model gave an average error of 12.2%.

For the Middle East, the Harvey Logistic model gave the best short term forecast, the Logistic model gave the best medium term forecast and the Harvey model gave the best long term forecasts. The Harvey model also gave the best overall forecasts with an average error of 3.1% while the Combined model gave the worst overall forecasts with an average error of 10.5%. In Africa, the Harvey model gave the best short term forecasts, while the Combined model gave the best medium and long term forecasts. Due to a very low and consistent error of just 1.8%, the Combined model was also ranked as the best overall model for this region. The ARIMA model gave the second best overall forecasts with an error of 2.2%, while the Logistic model gave the worst overall forecasts with an error of 6.6%.

In Developing Asia, the Harvey model gave the best short term forecasts, the ARIMA model gave the best medium term forecasts and the Combined model gave the best long term forecasts. The best overall forecasts were given by the ARIMA model with an average error of 4.9% while the worst overall forecasts were given by the Harvey Logistic model with an average error of 6.9%.

For the world total electricity consumption, the best short and medium term forecasts were given by the Harvey model. The Combined model gave the best long term forecasts. The Harvey model gave the best overall forecasts with a record low average error of just 0.87%. The second best overall forecasts were given by the Combined model with an average error of 1.27%. The Harvey model, Combined model and ARIMA model gave relatively competitive and consistently low average errors over the 9 years compared. The worst overall forecasts were given by the Logistic model.

10.5 COMPARISON OF FORECASTS

In this section, the forecasts given by each of the developed models from 2003 to 2017 for each of the regions are presented and compared with the EIA forecasts [EIA_2, 2003].

10.5.1 North America

Figure 10.13 shows the forecasts of all models from 2003 to 2017 for the industrialised countries of North America.

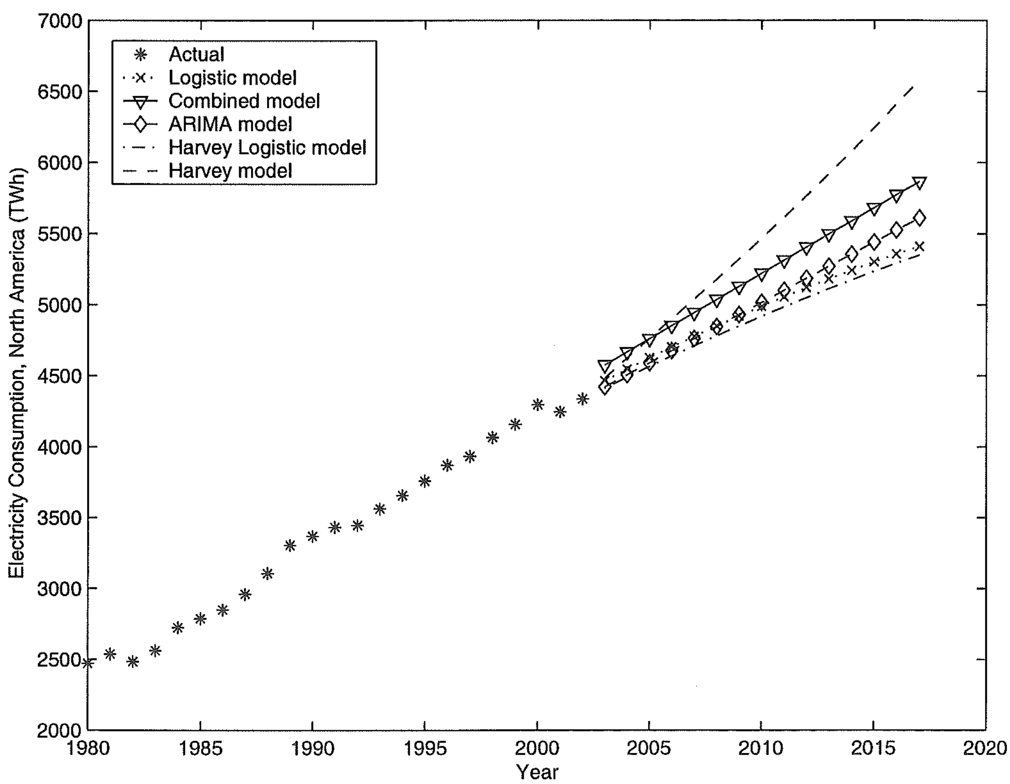

Figure 10.13 Comparison of forecasts for North America

The forecasts given by all models are generally very close to each other except for the Harvey model which gave the highest forecasts for this region. The Combined model and ARIMA model gave average of all the other forecasts while the Logistic and Harvey Logistic models gave the lowest forecasts. Table 10.6 shows the forecasts of these models as compared to the EIA forecasts for the years 2005, 2010 and 2015 for North America. The forecasts by the Harvey model are furthest from the EIA forecasts. The ARIMA model has given very close forecasts to the EIA forecasts especially for 2010 and 2015. The ARIMA model gave the most accurate overall forecasts for North America. From these projections, electricity consumption in North America is expected to grow and reach close to 5500 TWh by 2015.

Table 10.6 Comparison of forecasts with EIA projections for North America

Model	2005		2010		2015	
	TWh	*% Difference*	*TWh*	*% Difference*	*TWh*	*% Difference*
EIA	4422	-	4972	-	5512	-
Logistic	4625	4.6	4989	0.3	5301	-3.8
Combined	4760	7.6	5221	5.0	5681	3.1
ARIMA	4592	3.8	5016	0.9	5440	-1.3
Harvey Logistic	4564	3.2	4918	-1.1	5234	-5.0
Harvey	4763	7.7	5467	10.0	6244	13.3

10.5.2 Central and South America

Figure 10.14 shows the forecasts by all models for Central and South America, for 15 years ahead along with the actual consumption data from 1980 to 2002. The forecasts by the Harvey model are again the highest, while all the other four models gave relatively similar forecasts. Table 10.7 shows the forecasts for 2005, 2010 and 2015 for Central and South America along with the EIA projections. The forecasts by the overall best accurate Combined model for 2005 and that by the Logistic model for 2010 are very close (less than 1% error) to the EIA forecasts for these years. The forecasts from the ARIMA models are also very close to the EIA forecasts especially for 2005 and 2010. The forecasts by all models for 2015 are very different from those predicted by the EIA model. Rural electrification programs aimed to improve the standards of living and productivity in this region are believed to continue the electricity consumption trend throughout the projected period [EIA_1, 2004].

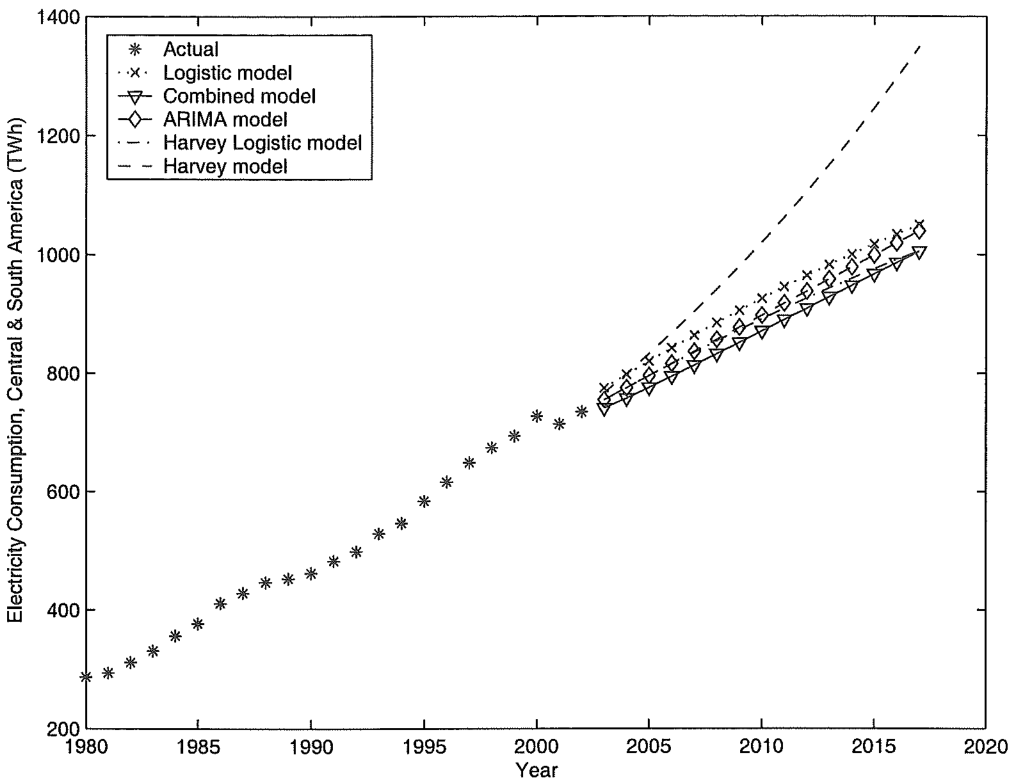

Figure 10.14 Comparison of forecasts for Central and South America

Table 10.7 Comparison of forecasts with EIA projections for Central and South America

Model	2005		2010		2015	
	TWh	*% Difference*	*TWh*	*% Difference*	*TWh*	*% Difference*
EIA	782	-	925	-	1081	-
Logistic	820	4.9	926	0.1	1017	-5.9
Combined	776	-0.8	871	-5.8	967	-10.5
ARIMA	795	1.7	897	-3.0	999	-7.6
Harvey Logistic	795	1.7	891	-3.7	976	-9.7
Harvey	832	6.4	1020	10.3	1246	15.3

10.5.3 Western Europe

Figure 10.15 shows the forecasts produced by all the developed models for electricity consumption in the Western Europe. The forecasts from all five models are close together. The Harvey model has given the highest forecasts while the Logistic model forecasted the lowest consumption. Table 10.8 shows the comparison of the forecasts with the EIA projections for selected years.

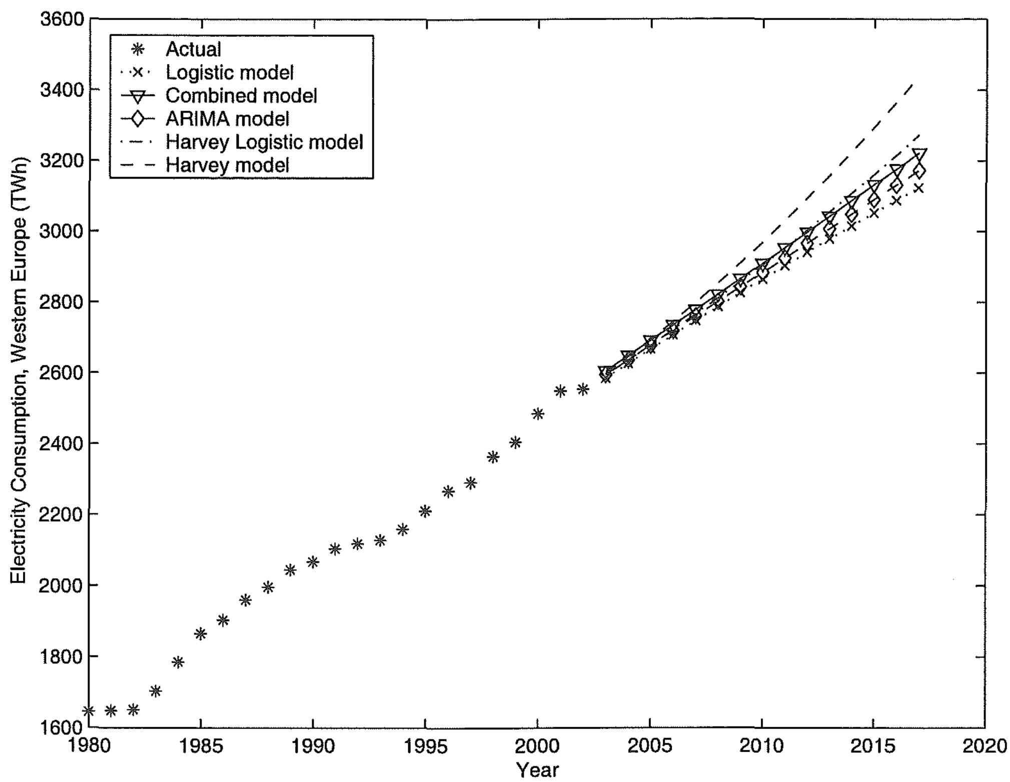

Figure 10.15 Comparison of forecasts for Western Europe

Table 10.8 Comparison of EIA forecasts with the developed model forecasts for Western Europe

Model	2005		2010		2015	
	TWh	*% Difference*	*TWh*	*% Difference*	*TWh*	*% Difference*
EIA	2664	-	2902	-	3156	-
Logistic	2667	0.1	2865	-1.3	3052	-3.3
Combined	2691	1.0	2910	0.3	3132	-0.8
ARIMA	2677	0.5	2884	-0.6	3090	-2.1
Harvey Logistic	2678	0.5	2905	0.1	3161	0.2
Harvey	2694	1.1	2970	2.3	3295	4.4

The forecasts given by all the models are very close to the EIA forecasts. The forecasts by the Harvey Logistic and Combined models are within or less than 1% of the EIA forecasts. In addition, the forecasts by the ARIMA model except for the forecasts of 2015 are also within the 1% margin. The forecasts by the best overall Harvey model are far from the EIA forecasts. The electricity consumption in this region is generally expected to grow at a relatively slow rate. Mature electricity infrastructure and slow population growth among the countries of this region could help the slow growth in demand for electricity in this region [EIA_1, 2004].

10.5.4 Industrialised Asia

There are only three countries in the Industrialised Asia region. They are Japan, Australia and New Zealand. Japan has the largest installed generation capacity with 235GW, as compared to Australia with 43GW and New Zealand with 9GW. Figure 10.16 shows the forecasts of electricity consumption for this region (which is essentially that for Japan) from 2003 to 2017 by all the developed models.

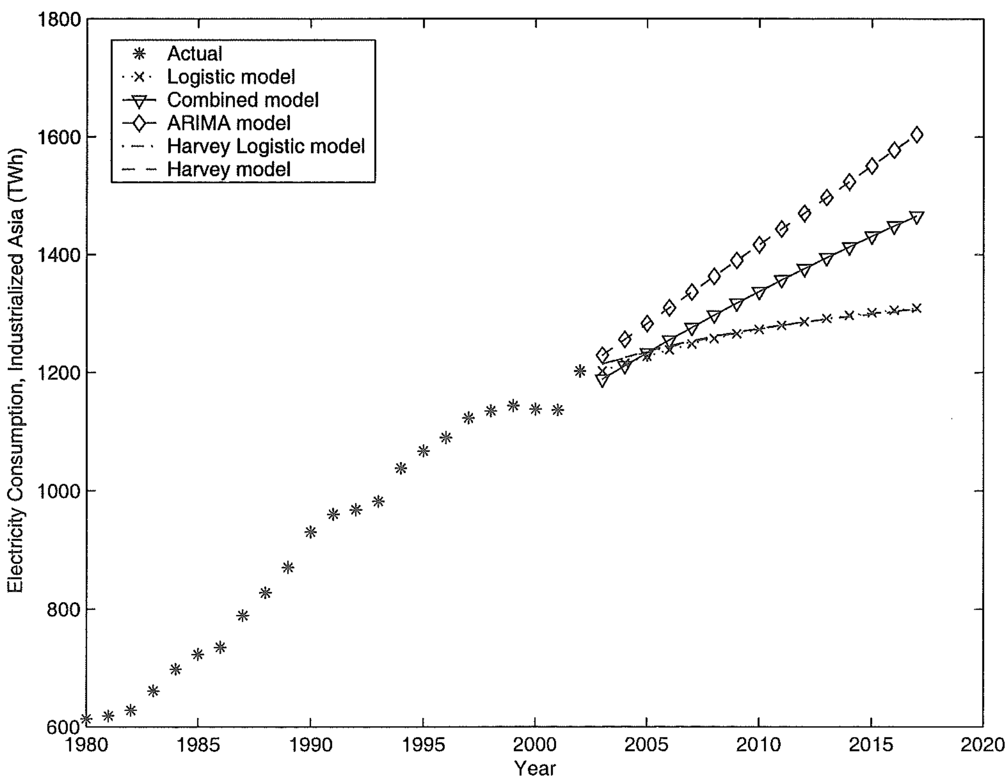

Figure 10.16 Comparison of forecasts for Industrialised Asia

Table 10.9 compares the forecasts with EIA projections for the years 2005, 2010 and 2015. The forecasts in this region are more diverse than those that have been presented so far. While the ARIMA models have given the highest forecasts, the forecasts from all the three growth curves are the lowest and the same throughout the whole period. The forecasts by the EIA and those by the best overall Combined model are very close with a difference less than or equal to 1%. The forecasts by the ARIMA model are higher and those by the growth curve models are lower than the EIA projections. The electricity consumption in this region is expected to grow at a moderately slow rate with mature electric power sectors in all three countries of this region.

Table 10.9 Comparison of the EIA forecasts with the developed models for Industrialised Asia

Model	2005		2010		2015	
	TWh	*% Difference*	*TWh*	*% Difference*	*TWh*	*% Difference*
EIA	1221	-	1326	-	1438	-
Logistic	1227	0.5	1273	-4.0	1301	-9.5
Combined	1233	1.0	1337	0.8	1431	-0.5
ARIMA	1283	5.1	1416	6.8	1550	7.8
Harvey Logistic	1234	1.1	1273	-4.0	1300	-9.6
Harvey	1236	1.2	1275	-3.8	1299	-9.7

10.5.5 Eastern Europe and the Former Soviet Union

Figure 10.17 shows the forecasts given by the developed models for Eastern Europe and the Former Soviet Union. The forecasts in this region are diverse. The ARIMA model predicts the highest increase in electricity consumption, while the Harvey Logistic and Harvey models predict a very slow rate of growth. The Logistic model predicts a slight decrease in the coming years. The Combined model predicts a fast decrease in electricity consumption in the years ahead. As indicated in Section 10.3.2 the Combined model for Eastern Europe and the Former Soviet Union merely satisfied the statistical requirements as compared to the proposed Combined models for the other regions. Thus, the projections from the Combined model are the least likely to be expected. Table

10.10 compares the developed model forecasts with the EIA forecasts for some selected years.

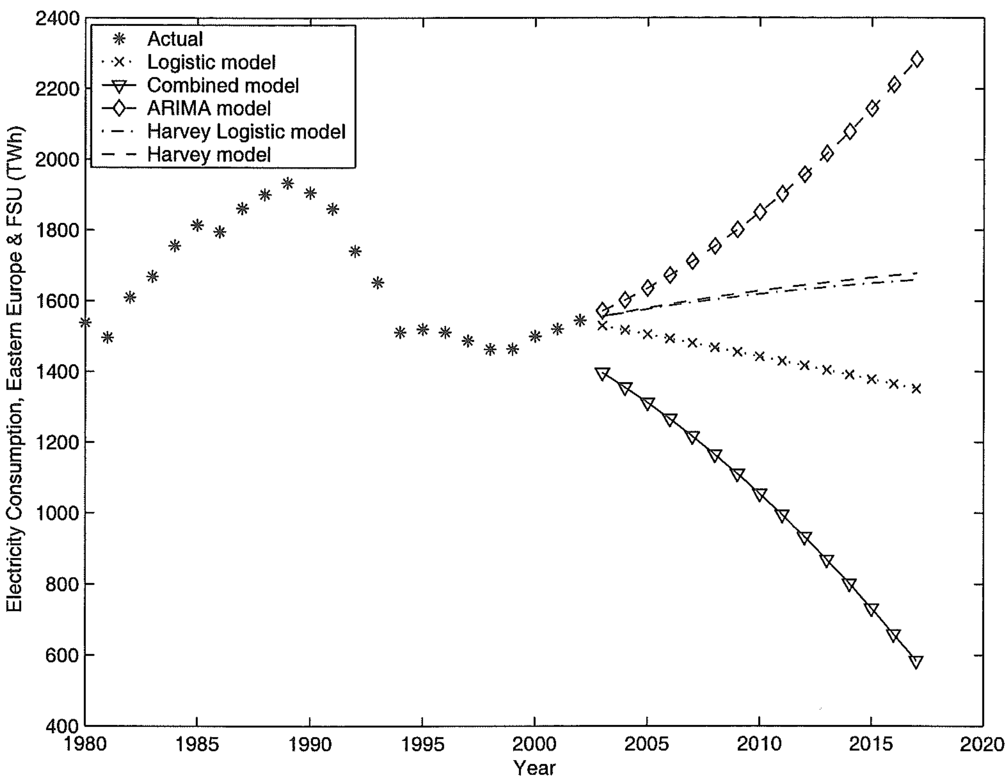

Figure 10.17 Comparison of forecasts for Eastern Europe and the Former Soviet Union

Table 10.10 Comparison of EIA projections with the developed models for Eastern Europe and the FSU

Model	2005		2010		2015	
	TWh	*% Difference*	*TWh*	*% Difference*	*TWh*	*% Difference*
EIA	1768	-	1982	-	2204	-
Logistic	1505	-14.9	1442	-27.2	1377	-37.5
Combined	1311	-25.8	1054	-46.8	731	-66.8
ARIMA	1635	-7.5	1850	-6.7	2143	-2.8
Harvey Logistic	1576	-10.9	1617	-18.4	1649	-25.2
Harvey	1579	-10.7	1628	-17.9	1665	-24.5

Most of the forecasts are very different from those predicted by EIA. However, the projections from the ARIMA model are comparable with the EIA forecasts. This suggests that EIA could be using a model similar to the ARIMA model. In addition, the most accurate model, among the developed models, for this region is the ARIMA model (Table 10.5).

10.5.6 Middle East

Figure 10.18 shows the forecasts for the Middle East by all the developed models.

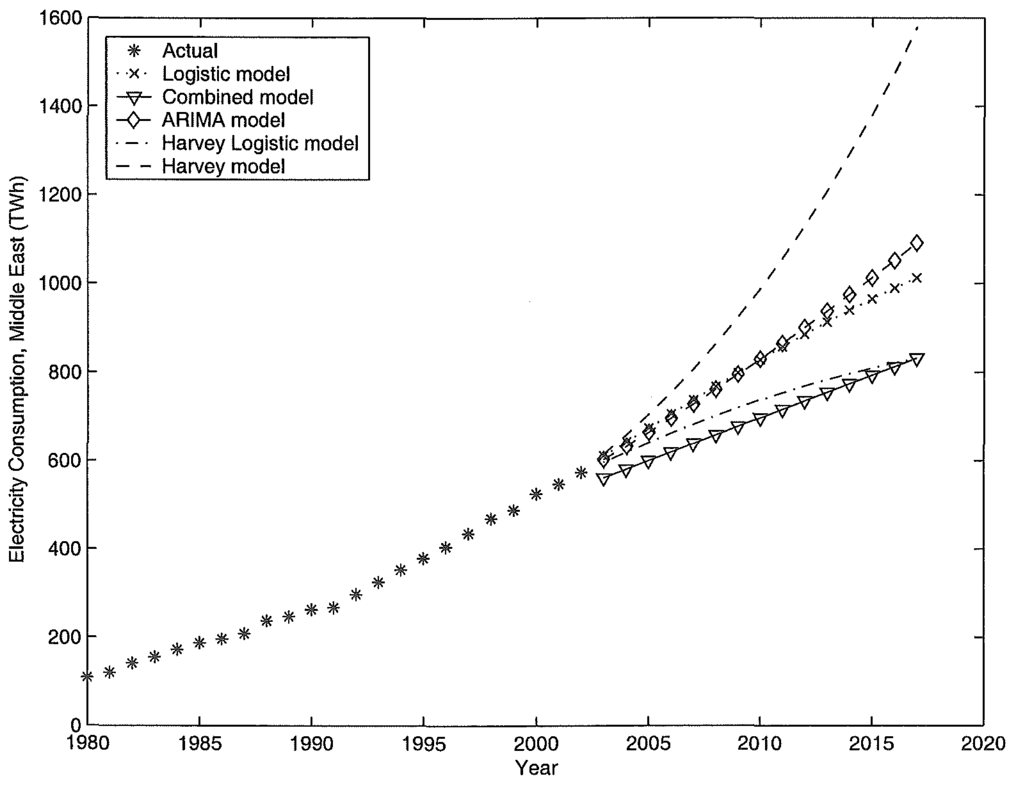

Figure 10.18 Comparison of forecasts for the Middle East

The Harvey model has given the highest forecasts, while the Combined and Harvey Logistic models have given the lowest but very similar forecasts. The forecasts by the ARIMA and Logistic models are also very similar. Table 10.11 compares these forecasts with the EIA projections for the years 2005, 2010 and 2015. The forecasts by all models are far from those predicted by the EIA models, except those by the

Combined model. The best overall Harvey model gave forecasts furthest from the EIA projections. High rates of population growth in this region are expected to lead to rapid demand in electricity consumption in the years ahead [EIA_1, 2004].

Table 10.11 Comparison of EIA forecasts with the developed models for Middle East

Model	2005		2010		2015	
	TWh	*% Difference*	*TWh*	*% Difference*	*TWh*	*% Difference*
EIA	558	-	665	-	784	-
Logistic	674	20.8	827	24.4	965	23.1
Combined	600	7.5	697	4.8	793	1.1
ARIMA	664	19.0	830	24.8	1013	29.2
Harvey Logistic	641	14.9	737	10.8	809	3.2
Harvey	705	26.3	988	48.6	1381	76.1

10.5.7 Africa

Figure 10.19 shows the forecasts given by the developed models for the countries of Africa. Apart from the slightly high forecasts by the Harvey model, all the other models have given very similar forecasts. Table 10.12 compares these forecasts with the EIA forecasts for Africa. For the year 2005, all models have given close forecasts to the EIA projections. In 2010 and 2015, all models except the Harvey model, underestimated the EIA projections. In many countries of Africa, the primary goal is to connect electric power supplies to populations [EIA_1, 2004]. The economies of many countries in this region are suffering from political corruption and lack of transparency, domestic unrest and warfare, and an AIDS epidemic, which have strained the economies of many nations in this region [EIA_1, 2004]. This has led to a very small percentage of many African countries with access to electricity. However, with efforts to attract international investment and to expand power grids through rural electrification programs, the region is expected to continue with the increase in electricity consumption in the forecasted period [EIA_1, 2004].

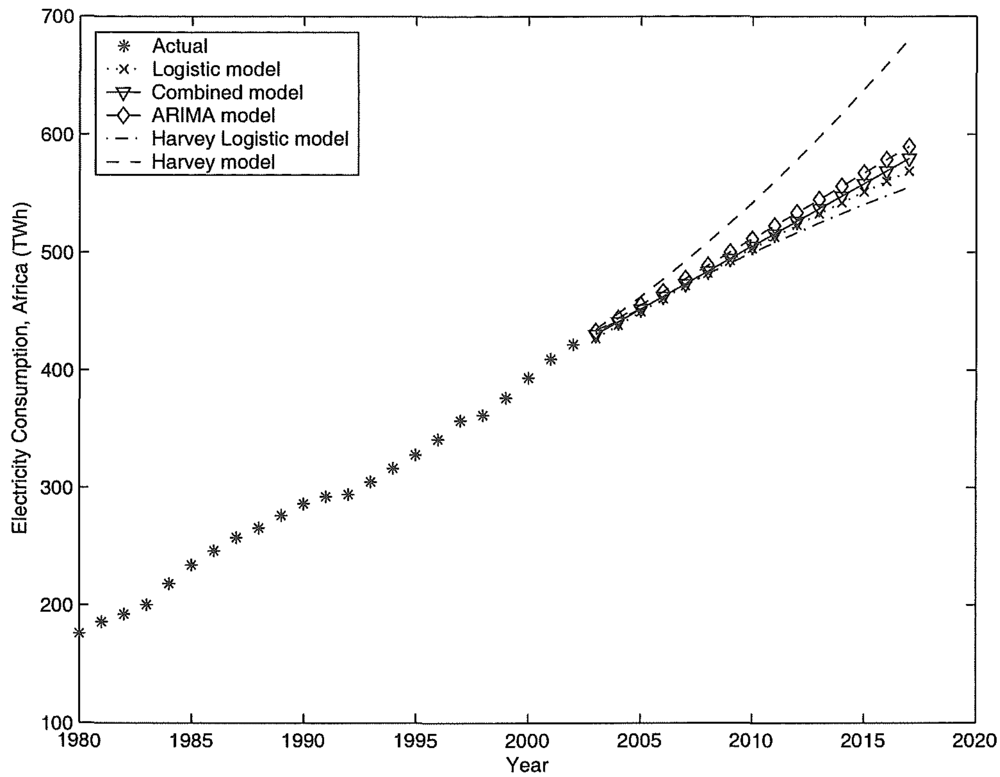

Figure 10.19 Comparison of forecast for Africa

Table 10.12 Comparison of the EIA forecasts with the developed models for Africa

Model	2005		2010		2015	
	TWh	*% Difference*	*TWh*	*% Difference*	*TWh*	*% Difference*
EIA	442	-	521	-	611	-
Logistic	450	1.8	504	-3.3	551	-9.8
Combined	452	2.3	505	-3.1	558	-8.7
ARIMA	456	3.2	512	-1.7	567	-7.2
Harvey Logistic	453	2.5	500	-4.0	541	-11.5
Harvey	463	4.8	542	4.0	638	4.4

10.5.8 Developing Asia

Figure 10.20 shows the forecasts given by all the developed models for the countries of developing Asia.

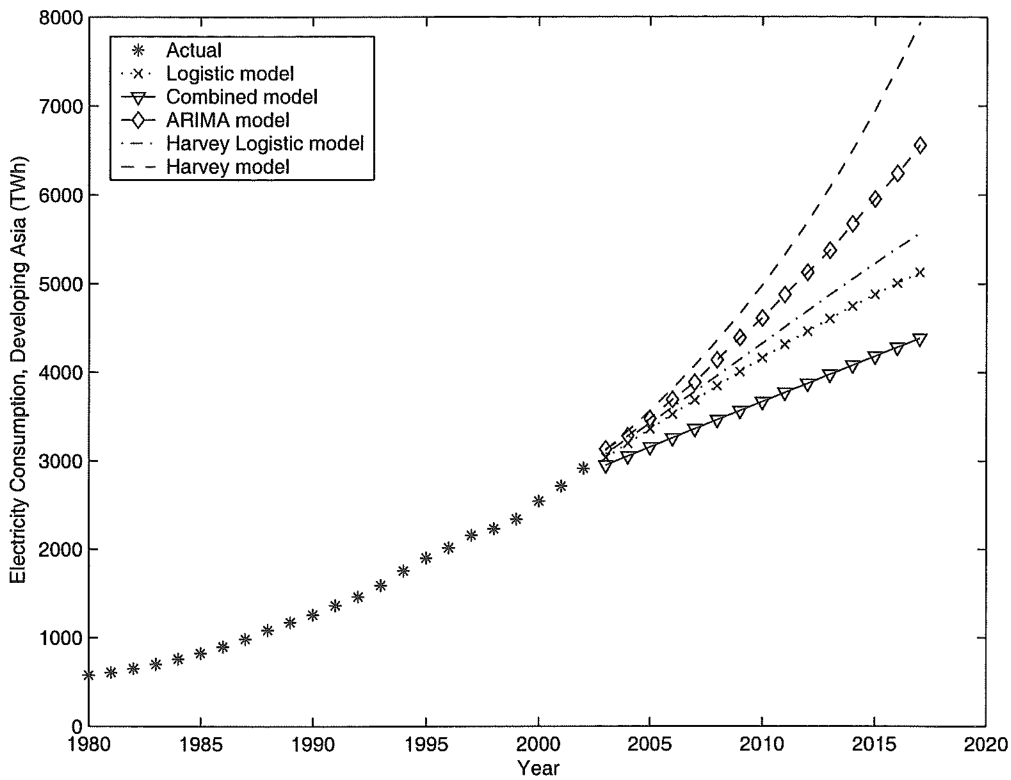

Figure 10.20 Comparison of forecasts for Developing Asia

The forecasts from these models are spread out. The highest forecasts are given by the Harvey model, while the Combined model gave the lowest consumption forecasts. The Harvey model and the ARIMA model predict an exponential increase in the growth while the other three models show a more uniform rate of growth. Table 10.13 compares these forecasts with the EIA forecasts for the years 2005, 2010 and 2015. The forecasts by the Combined model for 2005 and 2010 and those by the Logistic model for 2015 are close to the EIA forecasts. However, the forecasts from the other models, including the best overall ARIMA model, are generally different from those predicted by the EIA. Most of the developed models predict a slightly faster rate of growth than those predicted by the EIA. According to the EIA, the fastest rate of growth will be observed in the electricity sectors of the countries of developing Asia [EIA_1, 2004]. The majority of the increase in demand is expected in the residential sector. Robust growth in personal income in this region is expected to increase demand for newly purchased home appliances for air conditioning, refrigeration, cooking, and space and water heating [EIA_1, 2004]. The major electricity consumers in this region are China, India and South Korea.

Table 10.13 Comparison of EIA forecasts with the developed models for Developing Asia

Model	2005		2010		2015	
	TWh	*% Difference*	*TWh*	*% Difference*	*TWh*	*% Difference*
EIA	3103	-	3851	-	4697	-
Logistic	3359	8.3	4160	8.0	4877	3.8
Combined	3154	1.6	3667	-4.8	4180	-11.0
ARIMA	3474	12.0	4610	19.7	5950	26.7
Harvey Logistic	3424	10.3	4326	12.3	5227	11.3
Harvey	3566	14.9	4983	29.4	6949	47.9

10.5.9 World Total Electricity Consumption

Figure 10.21 shows the world total electricity consumption as forecasted by the five developed models.

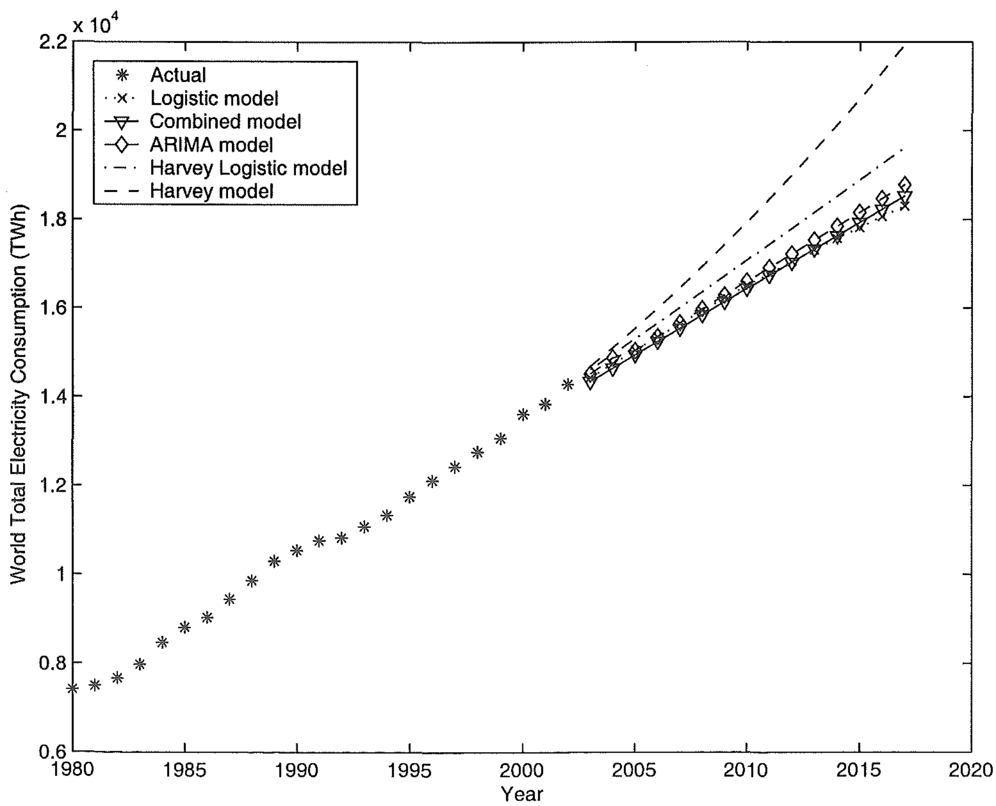

Figure 10.21 Comparison of forecasts for world total electricity consumption

The Logistic, Combined and ARIMA models gave relatively similar forecasts for fifteen years ahead. The Harvey model again predicted the highest rate of consumption. Table 10.14 compares the forecasts by these models with the EIA projections for selected years. The EIA forecasts are very similar to those predicted by the Harvey Logistic model. The forecasts of the other models are also not very far from these forecasts. The best overall Harvey model forecasts are slightly higher while the other three model forecasts are lower than those predicted by the EIA.

Table 10.14 Comparison of EIA forecasts with the developed models for world total electricity consumption

Model	2005		2010		2015	
	TWh	*% Difference*	*TWh*	*% Difference*	*TWh*	*% Difference*
EIA	14960	-	17144	-	19482	-
Logistic	15045	0.6	16500	-3.8	17819	-8.5
Combined	14942	-0.1	16435	-4.1	17927	-8.0
ARIMA	15036	0.5	16596	-3.2	18156	-6.8
Harvey Logistic	15307	2.3	17074	-0.4	18886	-3.1
Harvey	15540	3.9	17932	4.6	20717	6.3

It is expected that much of the growth in electricity demand in the world would come from the developing countries. Although the developing countries account for more than 75 percent of the world population, the electricity consumption in these countries is only one-third of the world's electricity consumption [EIA_1, 2004]. The developing countries are expected to have a robust economic growth in the coming years. This requires access to reliable supplies of electricity. The governments of many developing countries have recognised the need for their citizens to have access to electricity. As a result, various strategies have been implemented such as privatisation to increase investment in the electricity industry and enacting government policies to encourage investment from potential foreign participants [EIA_1, 2004]. In addition, rural electrification schemes are expected to be introduced both to improve the standard of living and to increase the productivity of rural communities.

The growth in electricity consumption in the industrialised world is expected to increase more slowly. The well established electricity sectors and gains in equipment efficiency in the industrialised countries are expected to slow down the growth in electricity consumption.

10.6 DISCUSSION

This section aims to discuss two main points observed in Sections 10.4 and Section 10.5 Firstly, it has been observed in Section 10.4.1 (Table 10.5) that although the forecasting accuracies given by the Harvey models are comparable to those of the Combined and ARIMA models, they are not significantly better than the ARIMA and Combined models, as compared to the performance of the Harvey model when applied to the selected countries (Chapters 6 to 9). Secondly, it has been observed that although the Harvey model's forecasts are comparable with those of the ARIMA and Combined models, its forecasts in Section 10.5 are generally higher than those of the other models.

While forecasting electricity consumption in New Zealand, electricity consumption data from 1943 to 1999 (March year 2000) are used giving a total of 57 data points. For the United States the electricity consumption data are available from 1949 to 2002 giving a total of 54 data points. In these cases the Harvey models have generally given better forecasts than the Combined or ARIMA models. In the United Kingdom the data are available from 1970 to 2002 with a total of 33 data points. In this case the Harvey model has given the best forecasts along with the Combined and Logistic models. In the case of the Maldives and in this chapter for world electricity consumption, the data are available from 1980 to 2002 giving a total of 23 data points. In these cases, the Harvey models or any other growth curve model, cannot be regarded as the best model. However, they are among the best models.

In general, using less data points, the ARIMA models have given better or comparable forecasts than the Harvey model. However, when more data points are available, the Harvey models have given better forecasts. When less data points are available the series is less likely to be observed as approaching maturity. The growth curves especially the Harvey model that is based on general modified exponentials [Harvey, 1984] see the electricity consumption pattern as in the early phase of growth. This results in higher values of consumption forecasts.

Although the Harvey model has performed relatively inaccurately in this chapter as compared to the case of New Zealand and the United States, it is expected that if more data points were available for the world electricity consumption, the model could give more accurate forecasts. This in turn is likely to result in more comparable and convincing forecasts by the Harvey model. However, as discussed before, this was not possible at the time of this research.

10.7 SUMMARY

In this chapter, world electricity consumption data has been categorised into eight regions to model and forecast electricity consumption. The forecasting models are applied to the electricity consumption data available for these regions and world total from 1980 to 2002. The VAL model was found to be unstable mainly due to the small number of the data points available. All the other models have been applied to the different regions and the world total electricity consumption. The models were then compared for forecasting accuracy. In most regions the ARIMA model gave the most accurate forecasts. However, the Combined model and Harvey model also gave very comparable forecasting accuracies. The best overall forecasts for the world total electricity consumption are given by the Harvey model.

The electricity consumption forecasts given by these models for the regions and world total were presented and compared with the Energy Information Administration, EIA forecasts. In some cases the forecasts by the best overall models for a particular region were in close agreement with the EIA projections while in other cases they were not. However, some of the developed models always gave forecasts close to the EIA forecasts when compared at some selected years. It is believed that the overall performances of the developed models, especially those of the growth curve models, could be further improved by using more historical data points.

Chapter 11

OVERALL COMPARISON & FINDINGS

11.1 INTRODUCTION

The developed electricity forecasting models have been applied to each of the four selected countries; New Zealand, the Maldives, the United States and the United Kingdom. They have also been applied to the electricity consumption in the various regions of the world and the world total electricity consumption. The performances of the models with respect to each of these data sets have been separately compared in the respective chapters previously. In this chapter, the overall performances of the models irrespective of the data sets are compared at the country and regional levels. This section also evaluates the best models for short, medium and long term forecasting in terms of their application to the various data sets. This will give a broader view on the overall performances of the models. However, as discussed in the previous chapters, the VAL model could not be applied to some of the data sets. Therefore, the VAL model will not be included in this comparison as this could lead to misleading results.

11.2 OVERALL PERFORMACE AT COUNTRY LEVEL

The forecasting accuracy is measured over the same nine year period for New Zealand, the United States and the United Kingdom, and for a five year period in the case of the Maldives. The overall mean absolute percentage error (MAPE) over the selected period is calculated for all the models for each of the data sets. The model that gives the lowest MAPE value for each of these data sets is ranked as the best model. Table 11.1 shows the number of times each of the models are ranked the overall best and second best when applied to the Domestic, the Non-Domestic and the Total electricity consumption of all the selected countries.

Table 11.1 Overall best and second best models for New Zealand, the Maldives, the United States and the United Kingdom

Model	Number of times each model is ranked		Total
	best	second best	
Logistic	1	2	**3**
Combined	1	4	**5**
ARIMA	2	2	**4**
Harvey Logistic	1	1	**2**
Harvey	7	2	**9**

The Harvey model has been ranked the best 7 times and second best 2 times for the four countries compared. The ARIMA was ranked best and second best twice. The Combined model was ranked the best once but second best four times. The Logistic and Harvey Logistic models were each ranked the best once. This suggests that the best overall electricity consumption forecasts are given by the Harvey model. The second best overall forecasts are given by the Combined and ARIMA models.

In general, the Harvey models have given very low MAPE errors over the nine year period compared. For the Total consumption of New Zealand, the United States, the United Kingdom and the Maldives the average errors by the respective Harvey models are 1.08%, 1.87%, 1.90 % and 4.43%. The second best Combined models gave errors of 3.3%, 3.00%, 1.84% and 3.3% for the New Zealand, the United States, the United Kingdom and the Maldives respectively while the corresponding ARIMA models gave errors of 1.54%, 4.68%, 3.94% and 3.69% respectively. Although the ARIMA and Combined models have been used frequently in electricity forecasting, these results show that the Harvey models have generally given rise to far better models among the countries compared in this research. This suggests that the Harvey models could play a significant role in electricity forecasting over the traditional ARIMA and regression techniques.

11.3 OVERALL PERFORMANCE AT WORLD REGIONAL LEVEL

In this section, the forecasting models are ranked to observe how well each of the individual models has performed irrespective of the world region to which the models are applied. This is done by counting the number of times each of the models has given the best or second best overall forecasts in terms of the lowest MAPE values for each of the regions and world total. The rankings are shown in Table 11.2.

Table 11.2 Individual model rankings for world electricity consumption

Model	Number of times each model is ranked		Total
	best	second best	
Logistic	0	3	3
Combined	3	1	4
ARIMA	3	3	6
Harvey Logistic	0	2	2
Harvey	3	0	3

Overall, the ARIMA gave the best or second best forecasts most number of times. The Combined model, followed closely by the Harvey and Logistic models, is ranked the second best overall model. Although the Logistic model is ranked as good as the Harvey model, it has never been the best overall model. Therefore, the three models ARIMA, Combined and Harvey in that order can be regarded as the best overall models to forecast electricity consumption in the regions of the world and world total.

11.4 SHORT, MEDIUM AND LONG TERM FORECASTING

Having applied the proposed electricity forecasting models to a large number of data sets, it could be important to analyse which models performs the best for each of the short term (1-3 years), medium term (4-6 years) and long term (7-9 years) forecasts. Therefore, the number of times each of the models gives the best or second best accuracy (lowest MAPE values) for each of the data sets (Chapters 7 to 10) for the short, medium and long terms are listed in Table 11.3. As for the previous sections, the VAL model is not used in this comparison as it was not applied to some of the data sets. The total number of counts is less for the long term, as the long term comparison is not made for the Maldives (Chapter 7).

Table 11.3 Best models for short, medium and long terms forecasts

Model	Number of times each model is ranked best or second best		
	short	medium	long
Logistic	5	4	6
Combined	5	10	13
ARIMA	12	8	4
Harvey Logistic	8	6	3
Harvey	12	14	10

The best models to forecast the short term are the ARIMA and Harvey models. The best model in the medium term forecasting is the Harvey model while the Combined model has given a very close second best. The Combined model is ranked the best to forecast the long term, while the Harvey model is ranked second best with very close results. Therefore, in terms of the applications of the models to the selected countries and regions of the world, the ARIMA and Harvey model are the best to forecast the short term while the Combined and Harvey models are the best to forecast the medium and the long term electricity consumption. Overall, Harvey is the only model that gave among the best results in the short, medium and long term forecasts.

11.5 OVERALL WORST MODELS

It may be argued that the ranking approach used in this chapter and the previous chapters, although reasonable, ignores the consequences of the poor predictions which may sometimes occur. A model giving average performance all the time is preferable to one that is excellent for say 50% of the time and very bad for the other 50% of the time, unless the poor performance conditions can be identified, and avoided, with confidence. The approach used in this research so far accounts for the best and the second best accurate models. It does not account for the number of times each of the models has given amongst the worst performances. Therefore, in this section, the number of times each of the models has given the worst and the second worst accuracies are counted to analyse the most inaccurate model overall.

Table 11.4 Number of times each of the models is ranked worst and second worst

Model	Country level	World	Total
Logistic	8	6	**14**
Combined	3	3	**6**
ARIMA	7	0	**7**
Harvey Logistic	5	6	**11**
Harvey	1	3	4

These results clearly suggest that the Harvey model has given the best results giving the worst results the least number of times (corresponding to worst results less than 10% of the time). While the Harvey model gave the worst accuracies only 4 times, the corresponding Combined and ARIMA models gave the worst accuracies 6 times and 7 times respectively. The table also shows that the Logistic model and the Harvey Logistic model are the overall worst models of all the models developed. These results are in close agreement with the best overall performances presented in Section 11.2 and Section 11.3, justifying the ranking approach and supporting the best overall results by the Harvey model.

11.6 COMPLEXITY OF THE MODELS

It is also important to have some idea of how easy or difficult it is to develop and apply the models to the different electricity consumption data. Often defining simplicity or complexity of models could be misleading as there is no standard definition distinguishing simple from complex mathematical structure [Smith, 1997]. Long [Long, 1995] described that the model complexity is not only affected by the mathematical structure of the model but by the number of factors that it takes into account and the ease with which the model can be explained to data users. Linear versus non-linear models or the degree of interaction among variables could also be considered as indicators of simplicity or complexity [Armstrong, 1985]. In this section, a model is referred to as complex as opposed to a simple model if the mathematical structure of the model is more complex and if it requires more time to apply the model to a particular data set.

The proposed Logistic, Harvey Logistic and Harvey models are based on various forms of growth curves. These models are mathematically very simple and can be very easily applied to the data set required. In this research, these models are developed using MATLAB software. Due to their simplicity, a single function for each of these models has been programmed that accepts a particular data set and gives the required forecasts. Therefore, the growth curve models are applied very easily.

The Combined model uses multiple linear regression technique. The technique involves selecting the best explaining variables to describe the historical electricity consumption data. This process requires some time and in some cases experience as well. Once the appropriate variables are selected, the mathematics involved is simple, although slightly more complex than the growth curve models. Therefore, the Combined model is developed using a separate program for each data set, as the variables used in one data set may be different from one another.

The ARIMA model is based on the Box-Jenkins methodology that consists of an organised set of procedures for analysing any time series. The ARIMA technique has been described as the most mathematically complex technique among many quantitative forecasting techniques including regression and growth curves [Farnum and Stanton, 1989]. There has been more evidence that the ARIMA model is a more complex technique [Smith, 1997] [Bianchi *et al.*, 1998]. In this research, the software package ITSM2000 [Brockwell and Davis, 2002] is used as an aid in developing the ARIMA models. Although this has reduced the complexity of the mathematics, making the series stationary and selecting the best model for the data still requires time and experience.

The VAL model employs both the regression and ARIMA technique in a growth curve model. As this model involves the three techniques, it is the most complex of all the models that has been used in this research. The explaining variables in the Combined models are usually forecasted using the ARIMA technique and therefore this is the second most complex technique. The growth curve models, Logistic, Harvey Logistic and Harvey are the simplest of all the models used in this research.

11.7 FINDINGS

11.7.1 Simple Models Performed Better

An overall finding by applying the developed models to electricity consumption is that the simple growth curve model, Harvey, has performed better or at the same level as the more complex Combined and ARIMA models. The performance of the Harvey model was even better at country level applications and especially when more data points are available. The Harvey model has also performed better in well matured electricity industries where more data points are available. This was true for New Zealand and the United States where more than 50 annual data points were used in each case. In the United Kingdom the number of data points available was less, although the industry is mature. This has degraded the performance of the Harvey model. Therefore, it was believed that the Harvey model is very effective for forecasting electricity consumption in matured electricity industries.

11.7.2 Performance of the ARIMA Model

The ARIMA model has generally given better forecasts than the other models when it was applied to the world regional data and for the Maldives. In all these cases the number of data points available was 23. However, the performance of the ARIMA model was worse when compared to the other models for the United Kingdom, the United States and New Zealand where the number of data points available are 37, 54 and 57 respectively. Therefore, it can be concluded that the ARIMA model has given better overall forecasts than the other models when less data points are available. This was true whether the data set was mature or not. This does not necessarily mean that using more data points leads to more inaccurate models. It can be seen from the results in Chapters 6 to 10 that the overall forecasting accuracies (plotted in terms of MAPE values) are generally lower when more data points are available. When more data points are available some of the models gave better results than the ARIMA model. When less data points are available, the other models gave relatively inaccurate forecasts than the ARIMA model.

11.7.3 Best Model Fit does not necessarily mean the Best Model

Throughout the application of the developed models, it was found that the model that gives the best fit to the historical data has not necessarily produced the best overall forecasts. However, in few instances this might have been otherwise. This is not a surprising result as many other researchers have had similar findings [Young, 1993] [Martino, 2003]. Therefore, it is now widely accepted that the best model fit does not necessarily mean that it is the best model. A good forecasting model will give a better fit to the future data, and not necessarily the best fit to the historical data [Martino, 2003].

11.7.4 Consistency of the Combined Model Forecasts

The Combined model that used economic and demographic variables has given an average accuracy in all the data sets irrespective of whether the data set available was long or short. The forecasting accuracy of the Combined model was usually at moderate levels but are not the best. The Combined model also gave among the best overall medium and long term forecasts. The forecasts from the Combined model were very consistent in that it kept on performing at around the same level whether it was applied to a mature or young industry, and small or large data sets. This indicated that the use of the selected variables has allowed it to perform more consistently as opposed to the other models.

11.8 DIFFERENCES IN THE ECONOMIES

The developed forecasting models have been applied to four different countries with many differences in the structure and size of their economies.

In the economy of the Maldives, tourism accounts for two-third of the gross domestic product (GDP), while fishing accounts for six percent [Whitaker, 2005]. Agriculture is limited due to poor soil conditions in the country. The main electricity supply from the capital island is generally independent of these activities. In the tourism industry, electricity to resorts is supplied by owners themselves. As far as the capital island of Male' is concerned, the main electricity consumption is in government offices, the construction industry and workshops and other main businesses. Residential electricity consumption accounts for a large proportion of the total electricity consumed.

In the United States, services accounts for approximately 80 percent of GDP in 2002, industry 18 percent and agriculture 2 percent [Turner, 2005]. As the leading industrial power in the world, the major industries are petroleum, steel, motor vehicles, aerospace, telecommunications, chemicals, electronics, food processing, consumer goods, fishing, lumber and mining [Wright, 2003]. In terms of electricity consumption in the United States, the residential sector consumes over a third of the total electricity in the country, while the commercial sector accounts for 30 percent and industrial sector accounts for 26 percent [EIA, 2003].

In the United Kingdom, services account for 74 percent of the GDP, while the contributions by the industry and agriculture are 25 percent and 1.4 percent respectively [Turner, 2005]. The major industries are machinery and transportation equipment, metals and food processing [Wright, 2003]. As compared to many other industrialised countries, the manufacturing sector in the United Kingdom has declined and accounts for 20 percent of GDP [Turner, 2005]. The electricity industry contributes about 1.3 percent of the GDP [Turner, 2005]. In 2000, 29 percent of the electricity in the country was consumed by the residential customers, 29 percent by the industrial users, and commercial and other users took the remaining 42 percent [Turner, 2005].

New Zealand has a diverse economy and enjoys strong manufacturing and service industries as well as a successful agricultural sector [Whitaker, 2005]. In 2001, services accounted for 69 percent of GDP, while the contributions by industry and agriculture were 23 percent and 8 percent [Turner, 2005]. The major industries in New Zealand are food processing, wood and paper products, wool, textiles, dairy products, iron and steel [Whitaker, 2005]. Agricultural products such as wheat, barley , fruits, vegetables, dairy products and meat accounts for 70 to 80 percent of exports of the country [Whitaker, 2005]. Although New Zealand in terms of various economic measures tends to be considered a developed economy, it is quite different from the other two developed countries, the United States and the United Kingdom, considered in this thesis. New Zealand is highly dependent on the export of commodity products which tends to make it have many of the properties of an "underdeveloped" or "developing" economy. Due to the emphasis on agriculture in New Zealand, the intensity of the use of electricity (see Chapter 2 for details) is higher than those economies based on elaborately transformed products, as is the case for most of the so called developed economies.

Even with large differences in economy, size and population of the countries, the performance of some of the models are relatively consistent for all countries. The most consistent results are given by the Harvey model which gave the best accuracies for New Zealand and the United States, and second best accuracies for the United Kingdom and the Maldives. Economic and demographic factors have not affected electricity consumption as much as expected for New Zealand, the United States and the Maldives where the Combined model (that used these variables) is ranked as the third or fourth accurate model. However, the use of these variables for the United Kingdom has significantly improved the performance of the Combined model, ranking it overall the best, indicating that the effect of these variables on electricity consumption in the United Kingdom is higher than for the other economies. The electricity consumption pattern in the United Kingdom has varied significantly compared to the other countries (see Chapter 9). This could also have contributed to the slightly different performance of the models for the United Kingdom.

The variations of models for the Maldives and for the various regions of the world are harder to explain mainly because of the limited number of data available. However, it can be concluded that the overall behaviour of the models are consistent and the use of these extra data sets have helped enormously to draw the general conclusions and explanations made in this thesis.

11.9 SUMMARY

In the comparison at the country levels the Harvey model was the best. The second best results were given by the ARIMA and the Combined models. In the regional level and world total electricity consumption, the ARIMA model was the best followed by the Combined and the Harvey models. It was also found that the Harvey model is the only model that gave among the best results in the short, medium and long term forecasting. In general, the simple Harvey model has performed better than or as good as the more complex ARIMA and Combined models in forecasting electricity consumption.

Chapter 12

CONCLUSIONS AND FUTURE WORK

12.1 CONCLUSIONS OF THE THESIS

As part of the background research and to justify the use of GDP and population in some of the developed models, the thesis initially analysed the issue of deregulation and electricity consumption by studying the variation in the patterns of electricity per capita, GDP per capita, electricity intensity, electricity intensity curves and electricity intensity factors for selected countries and regions of the world. This was aimed at studying the relationship that may exist between electricity consumption and the economic growth of a country or region. Although the link between economic growth and energy demand are strongly influenced by the stage of development and the standard of living in a given region, it was found that the link between economic growth and electricity consumption is stronger in the developing countries than those for the industrialised countries. In the developing countries, the economies grow as more new industries that generally contribute to the economic wealth emerge. In the industrialised countries, although the energy consumption remains high, energy use is more stable or changing more slowly. In addition, in the industrialised countries the chances for increased efficiency, due to replacement of old equipment with modern equipment is higher than those for the developing countries. This has contributed to a reduction in the energy intensity in the industrialised countries. A general trend of a decreasing intensity in the industrialised countries and increasing intensity in the developing countries was also observed.

As a second part of the background research, this thesis has outlined the issue of deregulation in the electricity industry with specific emphasis on the factors contributing to deregulation and the impacts it has had on the various electricity industries. Finally, the intensity and the electricity consumption patterns were studied to observe whether deregulation has affected the patterns of electricity consumption. Using aggregate electricity consumption data for the countries analysed, it was found that deregulation has no significant impact on electricity consumption patterns. Therefore, it was concluded that for countries where deregulation has been introduced or is in the process of being introduced, the use of the developed electricity forecasting models is acceptable and that the forecasts should not be affected.

After a thorough review of the literature on forecasting, six models for electricity forecasting were proposed. Three of these models were based purely on growth curves. They were the Logistic model, the Harvey Logistic model and the Harvey model. Thereafter, various econometric models including the proposed Combined model was described. The autoregressive integrated moving average (ARIMA) models were also proposed for electricity forecasting. Finally, the Variable Asymptote Logistic (VAL) model that utilised economic and demographic variables and used an ARIMA technique in the Logistic model was proposed. The various statistical tests that were used in analysing the electricity consumption forecasting models were also explained. The models were accepted for forecasting a particular electricity consumption data based on the results of these statistics.

Of the proposed models, the ARIMA models and regression models have been more frequently applied in electricity forecasting. The Logistic model has been rarely applied in electricity forecasting. The Harvey Logistic and Harvey models have not been previously applied to electricity forecasting. Although a modified Logistic model has been applied to electricity forecasting, the VAL model, which has some similarity to the modified Logistic model, is a new model proposed for electricity forecasting. The models were applied to electricity consumption in the various countries and regions of the world.

Initially the forecasting models were applied and developed for electricity consumption in New Zealand where only limited national forecasts are available. The models were compared for goodness of fit to the historical data and for forecasting accuracy in the short, medium and long term for each of the Domestic and the Non-Domestic sectors and the Total electricity consumption. Overall, the best forecasts for New Zealand were given by the Harvey models for both the Domestic and the Total electricity consumption and by the Harvey Logistic model for the Non-Domestic sector.

The forecasting models were applied and developed for electricity consumption in the Maldives. In this case, the best overall forecasts were given by the Harvey model for the Domestic sector and the ARIMA models for the Non-Domestic sector and Total electricity consumption.

The application of the models was extended to the United States of America. All models generally gave acceptable fits to the historical electricity consumption data. Comparison of model fit and forecasting accuracy showed that the Harvey model was the best in model fit as well as the best overall forecasting in the Domestic, the Non-Domestic and the Total electricity consumption of the United States. The worst forecasting accuracies were given by the Logistic model, followed by the ARIMA models.

The application of the models to the country levels were concluded by applying the models to the electricity consumption in the United Kingdom. Comparison of the forecasting accuracy revealed that the Logistic model, Harvey model and the Combined model were in general the best models among those developed for the United Kingdom. Although the Logistic model for the United Kingdom revealed poor model fit to the historical data, their forecasting accuracies were very close to the Harvey and Combined models.

In the next stage of the research, the developed models were applied to the world electricity consumption data that were categorised into eight regions. The VAL model was found to be unstable to these data sets mainly due to the small number of the data points available. All the other models have been applied to the different regions and the world total electricity consumption. Although the ARIMA model was ranked the best overall model, the Combined model and Harvey model also gave very comparable forecasting accuracies for these regions. In addition, the best overall forecasts for the world total electricity consumption were given by the Harvey model.

In addition to developing and comparing the accuracies of the electricity forecasting models, the thesis also presented the forecasts given by the developed models for the selected countries and regions of the world. Where forecasts were available from other sources for the same data sets, they were also compared with the forecasts given by the developed models. In most situations the forecasts by the most accurate models were comparable with the alternative forecasts available.

Overall, application of the models at a country level revealed that the simple Harvey model has performed better than the more complex ARIMA and Combined models. It was also found that in both the United States and the United Kingdom the ARIMA models gave the most inaccurate forecasts. However, the forecasts by the ARIMA models were the closest to the Energy Information Administration (EIA) forecasts for these two countries. This suggested that the EIA forecasts employ a technique similar to the ARIMA technique. In the regional level and world total electricity consumption, the ARIMA model was overall the best, followed by the Combined and the Harvey models. An overall comparison of the models involving all the data sets that had been used in this research indicated that the best models to forecast the short term were ARIMA and Harvey models, while the Combined and Harvey models were the best in the medium and long term forecasting. The Harvey model was the only model that gave among the best results to forecast short, medium and long term electricity consumption. Therefore, it was concluded that the simple Harvey model has performed better than or as good as the more complex ARIMA and Combined models.

It was also found that the simple growth curve model, especially the Harvey model, was very effective in forecasting electricity consumption in mature electricity industries. This was even better when the number of data points available was large. In addition, it was also found that the ARIMA models were better for forecasting electricity consumption when few data points were available. It was also found that the model that gives the best fit to the historical data was not always the most accurate model, supporting previous similar findings. Another finding was that the Combined model gave an average accuracy but the most consistent results in all the applications.

No matter how mathematically complex a model is, how sophisticated the method used is, how large the number of data points that are used or how powerful the computing is, it should be emphasised that forecasting is based on extrapolations or establishing past patterns or relationships. This research has shown that the performance of more simple models should be taken into account before the search for more complex models begins. The thesis has proposed very simple, economical, accurate and convincing forecasts by the Harvey model as compared to the more traditional and complex models. However, no matter how convincing the models are, they can only be verified with time.

12.2 FUTURE WORK

12.2.1 Growth Curve Models

This thesis has concentrated on studying electricity consumption using growth curve models. The research began by studying the Logistic model which was applied to electricity consumption data in New Zealand in the early 1980s. The analyses of the Logistic model revealed some inaccuracies and low forecasts caused by the prior estimate of the saturation level. This led to the search for models that are possibly more accurate. Therefore, two other growth curve models, the Harvey Logistic and the Harvey models, were proposed for electricity consumption. As concluded in the previous section, it was found that the forecasts by the Harvey model were generally better than or as good as the other models compared, including the well known ARIMA and regression techniques (Combined model).

A study by Young [Young, 1993] on comparing nine different growth curve models indicated that the Bass model [Bass, 1969] [Heeler and Hustad, 1980] [Tigert and Farivar, 1981], Harvey model and extended Riccati model [Levenbech and Reuter, 1976] are the better forecasting models when the upper limit to a data set is not known. Although these models have been around for a while they have not been specifically applied to electricity forecasting. The Harvey model that has been used in this research has given very convincing results when applied to electricity forecasting. Therefore, it is recommended that any future work on electricity forecasting should start by developing the other two models and comparing their results with the developed Harvey model.

12.2.2 Regression and ARIMA Models

The ARIMA models only use electricity consumption data while the regression models allow the use of extra variables in forecasting. Often a combination of these models is thought to produce more accurate models. This is done by regression with ARIMA errors that allows the advantages of regression with the powerful time series features of the ARIMA model [Makridakis *et al.*, 1998]. A more general extension of this technique is dynamic regression or transfer function models [Makridakis *et al.*, 1998]. In this research, the regression and ARIMA models that have been more frequently applied in electricity forecasting are used as benchmarks on the performances of the simple growth curve models. Therefore, no attempt was made to develop these combined techniques. However, the performances of these combined approaches are worth researching in the future for electricity consumption.

A strong linkage between economic growth and electricity consumption was observed in Chapter 2. Therefore, one would expect that the Combined model developed using GDP and population could generally outperform the other models. However, this was not necessarily the case when the models were compared. Although the Combined model was among the best in forecasting medium and long term, it gave average overall forecasts for most data sets. Therefore, the question whether the regression model needs improvement in the technique or reconsideration of the variables used is worth researching.

The multiple linear regression models proposed in this research assumed that the explanatory variables affect electricity consumption. However, these models do not take into account whether electricity consumption could affect these variables as well. This issue of feedback between the variables could also be analysed as part of the future work using multivariate autoregressive models [Makridakis *et al.*, 1998] to observe whether this approach leads to more accurate electricity consumption forecasts.

12.2.3 Neural Network Models

Artificial neural network (ANN) models are receiving wide acceptance in the electricity industry and are starting to replace the older technologies based on times series and ARIMA models, especially in short term load forecasting [Satish *et al.*, 2004] [Beccali *et al.*, 2004] [Dillon *et al.*, 1991] [Park *et al.*, 1991] [Bakirtzls, 1996] [Piraz *et al.*, 1996] [Kontanzad *et al.*, 1997] [Srinivasan *et al.*,1999] [Bakirtzis *et al.*, 1995] [Daneshdoost *et al.*, 1998] [Drezga and Rahman, 1998]. This is mainly due to their ability to learn complex relationships though a training process using historical data. Therefore, it could be important to search for neural network models that could effectively describe the medium and long term electricity forecasting more accurately than the existing electricity forecasting models.

12.2.4 Further Testing of VAL Model

One important finding of the thesis was that the proposed VAL model has not performed very well in some situations. In most of these cases it was found that the VAL model cannot be applied due to the few data points available to develop the model. In some cases it was also found that the VAL model cannot be effectively applied if the saturation levels are unstable, reflecting immaturity in that sector of the electricity industry. Therefore, more robust testing on the behaviours of the VAL model using mature and immature electricity consumption data with various data sizes could help to answer these issues more appropriately.

REFERENCES

Abdel-Aal, R.E. and Al-Garni, A.Z. (1997), Forecasting monthly electric energy consumption in Eastern Saudi Arabia using univariate time-series analysis, *Energy*, Vol. 22, Issue 11, pp. 1059-1069, November 1997.

Abraham, A., and Nath, B. (2001), A neuro-fuzzy approach for modelling electricity demand in Victoria, *Applied Soft Computing*, Vol.1, Issue 2, pp. 127-138, August 2001.

Abu-El-Magd, M.A., Hamoud, G.A., and Findlay, R.D. (2003), Application of the value based approach to the planning of customer delivery systems, *IEEE*, pp. 968-973, 2003.

Akaike, H. (1974), A new look at statistical model identification, *IEEE Transactions on Automatic Control*, AC-90, pp. 716-723, 1974

Alcantara, V., and Duarte, R. (2004), Comparison of energy intensities in European Union countries: Results of a structural decomposition analysis, *Energy Policy*, Vol. 32, pp.177-189, 2004.

Alcantara, V., and Duro, J.A. (2004), Inequalities of energy intensities across OECD countries: a note, *Energy Policy*, Vol. 32, pp. 1257-1260, 2004.

Al-Alawi, S.M., and Islam, S.M. (1996), Principles of electricity demand forecasting: Part 1 Methodologies, *Power Engineering Journal*, Vol. 10, Issue 3, pp. 139-143, 1996.

Al-Kandari A.M., Soliman S.A., and El-Hawary M.E. (2004), Fuzzy short-term electric load forecasting, *International Journal of Electrical Power and Energy Systems*, Vol. 26, No. 2, pp. 111-22, 2004.

Alvey, T.G., and Cheung, K.W. (2000), Deregulation impacts and outcomes in competitive electricity markets, *Proceedings of the 5th International Conference on Advances in Power System Control*, Operation and Management, APSCOM 2000, Hong Kong, pp. 561-565, October 2000.

Andersen, T.J., and Remedios, A.J. (2003), Strategising in the deregulating energy markets: Two steps forward, one step back, and where next?, *The Electricity Journal*, August/September 2003, pp. 86-94, 2003.

Anderson, R.L. (1942), Distribution of the serial correlation coefficient, *Annals of Mathematical Statistics*, 13, pp.1-13, 1942.

Ang, B.W., and Zhang, F.Q. (2000), A survey of index decomposition analysis in energy and environmental studies, *Energy*, Vol. 25, pp.1149-1176, 2000.

Armstrong, J.S. (2001), Extrapolation for time-series and cross-sectional data in *Principles of Forecasting* by Armstrong, J.S , Kluwer Academic Publishers, USA, 2001.

Armstrong, J.S. (1985), *Long Range Forecasting*, John Wiley, New York, 1985.

Ayeni, B.J. and Pilat, R. (1992), Crude oil reserve estimation: An application of the autoregressive integrated moving average (ARIMA) model, *Journal of Petroleum Science and Engineering*, Vol. 8, Issue 1, pp. 13-28, July 1992.

Bakirtzis, A.G., Theocharis, J.B., Kiartzis, S.J., and Satsios, K.J. (1995), Short-term load forecasting using fuzzy neural networks, *IEEE Trans. Power Syst.*, Vol. 10, pp. 1518–1524, Aug. 1995.

Bakirtzls, A.G., Petridls, V., Klartzis, S.J., Alexladls. M.C., and Malssls, A.H. (1996), A neural network short term load forecasting model for the Greek power system, *IEEE Trans. Power Syst.*, Vol. 11, pp. 858–863, May 1996.

Bartlet, M.S. (1946), On the theoretical specification of sampling properties of autocorrelated time series, *Journal of the Royal Statistical Society*, Series B., 8, pp. 27., 1946.

Bass, F.M. (1969), A new product growth for model consumer durables, *Management Science*, Vol. 15, No.5, pp. 215- 227, 1969.

Beccali, M., Cellura, M., Lo Brano, V., and Marvuglia, A. (2004), Forecasting daily urban electric load profiles using artificial neural networks, *Energy Conversion and Management*, Vol. 45, Issues 18-19, pp. 2879-2900, November 2004.

Becken, S., Frampton, C., and Simmons, D. (2001), Energy consumption patterns in the accommodation sector – the New Zealand case, *Ecological Economics*, Vol. 39, pp. 371-386, 2001.

Bewley, R. and Fiebig, D.G. (1998), A flexible logistic growth model with applications in telecommunications, *International Journal of Forecasting*, Vol. 4, pp. 177-192, 1988.

Bewley, R. and Griffiths, W.E. (2003), The penetration of CDs in the sound recording market: issues in specification, model selection and forecasting, *International Journal of Forecasting*, Vol. 19, pp.111-121, 2003.

Bhargava, S., Bhargava, R. and Jain, A. (1991), Requirement of dimensional consistency in model equations: Diffusion models incorporating price and their applications, *Technological Forecasting and Social Change*, Vol. 41, pp. 177-188, 1991.

Bhattacharyya, S.C., and Ussanarassamee, A. (2003), Changes in energy intensities of Thai industry between 1981 and 2000: a decomposition analysis, *Energy Policy*, ARTICLE IN PRESS, 2003.

Bianchi, L., Jarrett, J., and Hanumara, R.C. (1998), Improving forecasting for telemarketing centers by ARIMA modelling with intervention, *International Journal of Forecasting*, Vol. 14, pp. 497-504, 1998.

Binroth, W., Burshtein, I., Harboush, R.K. and Hartz, J.R. (1979), A comparison of commodity price forecasting by Box-Jenkins and regression-based techniques, *Technological Forecasting and Social Change*, Vol. 14, pp.169 – 180, 1979.

Birol, F., and Argiri, M. (1999), World energy prospectus to 2020, *Energy*, Vol. 24, Issue 11, pp. 905-918, 1999.

Boas, A.H. (1963), Modern mathematical tools for optimisation, Part 3, *Chemical Engineering*, pp. 105-108, February 4, 1963.

Bodger, P.S and Tay, H.S (1987), Logistic and energy substitution models for electricity Forecasting : A comparison using New Zealand consumption data, *Technological Forecasting and Social Change*, Vol. 31, pp. 27-48, 1987.

Bodger, P.S. (1984), Electricity intensity factor: An alternative long term forecasting model, *IPENZ Conference*, Hasting, New Zealand, Paper 48/84, February 13-17, 1984.

Borenstein, S., and Bushnell, J. (2000), Electricity restructuring: Deregulation or regulation?, *Regulation*, Vol. 23, No. 2, pp. 46-52, 2000.

Boscheck, R. (1994), Deregulating European electricity supply: Issues and implications, *Long Range Planning*, Vol. 27, No. 5, pp. 111-123, 1994.

Bowerman, B.L. and O'Connell, R.T. (1993), *Forecasting and Time Series: An Applied Approach*, Third Edition, Duxbury Press, Belmont, California, 1993.

Box, G.E.P., and Jenkins, G.M. (1970), *Time Series Analysis: Forecasting and Control*, San Francisco, Holden-Day, 1970.

Box, G.E.P., and Pierce, D.A. (1970), Distribution of the residual autocorrelations in autoregressive-integrated moving-average time series models, *Journal of the American Statistical Association,* Vol. 65, pp. 1509-1526, 1970.

Box, G.E.P., Jenkins, G.M. and Reinsell, G.C. (1994), *Time Series Analysis: Forecasting and Control*, 3rd ed., Englewood Cliffs, N.J., Prentice Hall, 1994

Brockwell, P.J., and Davis, R.A. (2002), *An Introduction to Time Series and Forecasting*, New York, , Springer-Verlag, 2002.

Brunekreeft, G., and Keller, K. (2000), The electricity supply industry in Germany: market power or power of the market?, *Utilities Policy*, Vol. 9, pp. 15-29, 2000.

Bushnell, J. (2004), California's electricity crisis: a market apart?, *Energy Policy*, Vol. 32, pp. 1045-1052, 2004.

Canarella, G. and Pollard, S.K. (1989), Unanticipated monetary growth, output, and the price level in Latin America: An empirical investigation, *Journal of Development Economics*, Vol. 30, Issue 2, pp. 345-358, April 1989.

Carrillo, M. and Gonzalez, J.M. (2002), A new approach to modelling sigmoid curves, *Technological Forecasting and Social Change*, Vol. 69, pp. 233-241, 2002.

Chatfield, C. (2000), *Time Series Forecasting* , Chapman & Hall/CRC, USA, 2000.

Chavez, S.G., Bernat, J.X. and Coalla, H.L. (1999), Forecasting of energy production and consumption in Austrias (northern Spain), *Energy*, Vol. 24, Issue 3, pp. 183–198, March 1999.

Chen, H., Canizares, C.A., and Singh, A. (2001), ANN-based short-term load forecasting in electricity markets, *IEEE Power Engineering Society Winter Meeting 2001*, Vol. 2 , pp. 411 – 415, 28 Jan.-1 Feb. 2001.

Cohen. C., Lenzen, M., and Schaeffer, R. (2003), Energy requirements of households in Brazil, *Energy Policy*, Vol. 33, pp. 555-562, 2005.

Cornillie, J., and Fankhauser, S. (2004), The energy intensity of transitional countries, *Energy Economics*, Vol. 26, pp. 283-295, 2004.

Cranage, D.A., and Andrew, W.P. (1992), A comparison of time series and econometric models for forecasting restaurant sales, *International Journal of Hospitality Management*, Vol. 11, Issue 2, pp. 129-142, May 1992.

Daneshdoost, M., Lotfalian, M., Baumroonggit, G., and Ngoy, J.P. (1998), Neural network with fuzzy set-based classification for short-term load forecasting, *IEEE Trans. Power Syst.*, Vol. 13, Nov. 1998.

Darbellay, G.A., and Slama, M. (2000), Forecasting the short-term demand for electricity: Do neural networks stand a better chance?, *International Journal of Forecasting*, Vol. 16, pp. 71-83, 2000.

Department of Statistics (2000 & 2002), *The New Zealand Official Year Book 2002, 2000*, Wellington, N.Z. Govt. Printer.

Dillon, T.S., Sestito, S., and Leung, S. (1991), Short term load forecasting using an adaptive neural network, *International Journal of Electrical Power and Energy Systems,* Vol. 13, Aug. 1991.

Dincer, I. (1997), Energy and GDP analysis of OECD countries, *Energy Conversion and Management*, Vol. 38, No. 7. pp. 685-696, 1997.

Doms, M.E., and Dunne, T. (1995), Energy intensity, electricity consumption, and advanced manufacturing-technology usage, *Technological Forecasting and Social Change*, Vol. 49, pp. 297-310, 1995.

Dorn, H.F. (1950), Pitfalls in population forecasts and forecasts and projections, *Journal of the American Statistical Association*, Vol. 45, pp. 311-334, 1950.

Drezga, I., and Rahman, S. (1998), Input variable selection for ANN-based short-term load forecasting, *IEEE Trans. Power Syst.*, Vol. 13, pp.1238–1244, Nov. 1998.

DTI_1 (2004), Department of Trade and Industry, *Energy Consumption in the United Kingdom*, London, July 2002, Available online at: http://www.dti.gov.uk/energy/inform/energy_consumption/index.shtml, at 19 May 2004.

DTI_2 (2004), Department of Trade and Industry, *Energy Statistics: Electricity*, UK, Available online at: http://www.dti.gov.uk/energy/inform/energy_stats/electricity/index.shtml, at 19 May 2004.

DTI_3 (2004), Department of Trade and Industry, *Chapter 5: Electricity in Digest of UK Energy Statistics 2003*, pages 115 – 130, UK, Available online at: http://www.dti.gov.uk/energy/inform/dukes/index.shtml, at 19 May 2004.

DTI_4 (2004), Department of Trade and Industry, *Energy Trends, UK*, Available online at: http://www.dti.gov.uk/energy/inform/energy_trends/electricitysince1920.xls, at 20 May 2004.

DTI_5 (2004), Department of Trade and Industry, *Energy Statistics: Total Energy*, UK, Available online at: http://www.dti.gov.uk/energy/inform/energy_stats/total_energy/dukes1_1_4.xls, on 20 May 2004.

Egelioglu, F., Mohamad, A.A., and Guven, H. (2001), Economic variables and electricity consumption in Northern Cyprus, *Energy*, Vol. 26, pp. 355-362, 2001.

EIA (2003), Energy Information Administration, *Annual Energy Review 2002*, Washington DC, October 2003, Available online: http://www.eia.doe.gov/emeu/aer/contents.html, at 5 May 2004.

EIA (1997), Energy Information Administration, Electricity restructuring and privatisation in the United Kingdom in *Electricity Reform Abroad and U.S Investment*, page 13-38, Washington, September 1997, Available online at: http://www.eia.doe.gov/emeu/international/electric.html#IntlRestructuring, at 19 May 2004.

EIA (1996), Energy Information Administration, *Privatisation and the Globalisation of Energy Markets*, US Department of Energy, Washington DC, October 1996.

EIA (2000), Energy Information Administration, *The Changing Structure of the Electric Power Industry 2000: An Update*, US Department of Energy, Washington DC, October 2000.

EIA_1 (2004), Energy Information Administration, *International Energy Outlook 2004*, Washington DC, 2004, Available online: http://www.eia.doe.gov/oiaf/ieo/index.html, on 20 July 2004.

EIA_2 (2004), Energy Information Administration, *International Energy Annual 2004*, Washington DC, 2004, Available online: http://www.eia.doe.gov/emeu/iea/contents.html, on 20 July 2004.

EIA_2 (2003), Energy Information Administration, *International Energy Outlook 2003*, Washington DC, 2003, Available online: http://www.eia.doe.gov/emeu/international/electric.html#ConsumptionForecasts, at 7 May 2004.

EIA_3 (2004), Energy Information Administration, Energy *in the United States : 1635-2000*, Available online: http://www.eia.doe.gov/emeu/aer/eh/frame.html, at 5 May 2004.

EIA_4 (2004), Energy Information Administration, *United Kingdom Country Analysis Brief*, April 2004, USA, Available online at: http://www.eia.doe.gov/emeu/cabs/uk.html, at 19 May 2004.

El-Bassiouni, M.Y., and El-Habashi, M.H. (1991), Forecasting compulsory motor insurance claims in Kuwait, *Insurance: Mathematics and Economics*, Vol. 10, pp. 85-92, 1991.

Elkateb, M.M., Solaiman, K., and Al-Turki, Y. (1998), A comparative study of medium-weather-dependent load forecasting using enhanced artificial/fuzzy neural network and statistical techniques, *Neurocomputing*, Vol. 23, pp. 3-13, 1998.

ESRC (1992), Electricity Shortage Review Committee, *The Electricity Shortage 1992*, Department of Prime Minister and Cabinet, Wellington, New Zealand, 1992.

EECA (2000), Energy Efficiency and Conservation Authority (EECA), *Energy-wise monitoring quarterly, household sector*, Issue 15, June 2000, Wellington, New Zealand, 2000.

Evans, L., Arthur Grimes, A., Wilkinson, B., and Teece, D. (1996), Economic reform in New Zealand 1984-95: The pursuit of efficiency, *Journal of Economic Literature*, Vol. 36, pp. 1856-1902, 1996.

Farnum, N.R., and Stanton, L.W. (1989), *Quantitative Forecasting Methods*, PWS-KENT Publishing Co., Boston, 1989.

Fatai, K., Oxley, L., and Scrimgeour, F.G. (2004), Modelling the causal relationship between energy consumption and GDP in New Zealand, Australia, India, Indonesia, The Philippines and Thailand, *Mathematics and Computers in Simulation*, Vol. 64, pp. 431-445, 2004.

Fildes, R. and Lusk, E.J. (1984), The choice of a forecasting model, *OMEGA: International Journal of Management Science*, Vol. 12, No.5, pp. 427-435, 1984.

Fildes, R. (1983), An evaluation of Bayesian forecasting, *Journal of Forecasting*, Vol. 2, pp. 137-150, 1983.

Fildes, R., and Howell, S. (1979), On Selecting a Forecasting Model, in *TIMS Studies in the Management Sciences*, Vol. 12, S. Makridakis and S.C. Wheelright, eds., North Holland, Amsterdam, 1979.

Fisher, J.C. & Pry, R.H. (1971), A simple substitution of technological change, *Tech. Forecast & Social Change*, Vol. 3, pp. 75-88, 1971.

Fisher-Vanden, K., Jefferson, G.H., Liu, H., and Tao, Q. (2004), What is driving China's decline in energy intensity?, *Resource and Energy Economics*, Vol. 26, pp.77-97, 2004.

Focacci, A. (2005), Empirical analysis of the environmental and energy policies in some developing countries using widely employed macroeconomic indicators: The cases of Brazil, China and India, *Energy Policy*, Vol. 33, pp. 543-554, 2005.

Frank, L.D. (2003), An analysis of the effect of the economic situation on modelling and forecasting the diffusion of wireless communications in Finland, *Technological Forecasting and Social Change*, ARTICLE IN PRESS, 2003.

Franses, P.H. (2002), Testing for residual autocorrelation in growth curve models, *Technological Forecasting and Social Change*, Vol. 69, Issue 2, pp. 195-204, 15 February 2002.

Fung, Y.H. and Tummala, V.M.R. (1993), Forecasting of electricity consumption: A comparative analysis of regression and artificial neural network models, *IEE 2nd International Conference on Advances in Power System Control*, Operation and Management, pp. 782-787, Hong Kong, 1993.

Ghosh, S. (2002), Electricity consumption and economic growth in India, *Energy Policy*, Vol. 30, pp. 125-129, 2002.

Giovanis, A.N., and Skiadas, C.H. (1999), A stochastic logistic innovation diffusion model studying the electricity consumption in Greece and the United States, *Technological Forecasting and Social Change*, Vol. 61, pp.235-246, 1999.

Global Insight, Inc. (2003), *European Energy Outlook*, Vol. 1, Lexington, MA, April 2003.

Gross, G. and Galiana, F.D. (1987), Short-Term load forecasting, *Proc. IEEE*, Vol. 75, No.12, pp.1558-1573, December 1987.

Gunn, C. (1997), Energy efficiency vs economic efficiency? New Zealand electricity sector reform in the context of the national energy policy objective, *Energy Policy*, Vol. 25, No. 4, pp. 445-458, 1997.

Haar, B.W. (2004), Impact of deregulation on the task of commission control, *Utility Policy*, Vol. 12, pp. 193-202, 2004.

Hagan, M.T., and Behr, S.M. (1987), The time series approach to short term load forecasting, *IEEE Transactions on Power Systems*, Vol. 2, pp.785-791, August 1987.

Hamalainen, R.P., Mantysaari, J., Ruusunen, J., and Pineau, P. (2000), Cooperative consumers in a deregulated electricity market – dynamic consumption strategies and price coordination, *Energy*, Vol. 25, p.857-875, 2000.

Hankinson, G.A., and Rhys, J.M.W. (1983), Electricity consumption, electricity intensity and industrial structure, *Energy Economics*, Vol. 5, p.146-152, 1983.

Harris, J.L. and Liu, L. (1993), Dynamic structural analysis and forecasting of residential electricity consumption, *International Journal of Forecasting*, Vol. 9, pp. 437-455, 1993.

Harvey, A.C. (1984), Time series forecasting based on the logistic curve, *Journal of the Operational Research Society*, Vol. 35, No. 7, pp. 641-646, 1984

Harvey, A.C. (1993), *Time Series Models*, Second Edition, The MIT Press, Cambridge, Massachusetts, Second Edition, 1993.

Harvey, V.A., and Gibbs, D.M.H. (1980), A technique for long term industry forecasting, *Paper presented at the ANZAAS Jubilee Congress*, Adelaide, 16 May 1980.

Heeler, R.M., and Hustad, T.P. (1980), Problems in predicting new product growth for consumer durables, *Management Science*, Vol. 26, pp. 1007-1020, 1980.

Hessari, F.A. (2004), Sectoral energy consumption in Iran, *Renewable & Sustainable Energy Reviews*, ARTICLE IN PRESS, 2004.

Hirschhausen, C., and Andres, M. (2000), Long-term electricity demand in China – From quantitative to qualitative growth?, *Energy Policy*, Vol. 28. pp. 231-241, 2000.

Hsu, C., and Chen, C. (2003), Regional load forecasting in Taiwan - Applications of artificial neural networks, *Energy Conversion and Management*, Vol. 44, Issue 12, pp. 1941-1949, July 2003.

Hsu, G.J.Y., and Liu, M.C. (1991), Energy consumption and resultant air pollution: An ARIMA forecasting model for Taiwan, *Energy Systems and Policy*, Vol. 15, pp.137-144, 1991.

Huang, H., Hwang, R., and Hsieh, J. (2002), A new artificial intelligent peak power load forecaster based on non-fixed neural networks, *International Journal of Electrical Power and Energy Systems*, Vol. 24, No. 3, pp. 245-50, 2002.

Huang, J.P. (1993), Electricity consumption and economic growth: A case study of China, *Energy Policy*, Vol. 21, Issue 6, pp. 717-720, 1993.

Hyde, O., and Hodnett, P.F. (1997), An adaptive automated procedure for short-term electricity load forecasting, *IEEE Transactions on Power Systems*, Vol. 12, No. 1, pp. 84-94, February 1997.

Ilkka Virtanen, I. and Yli-Olli, P. (1987), Forecasting stock market prices in a thin security market, *Omega*, Vol. 15, Issue 2, pp. 145-155, 1987.

Infield, D.G., and Hill, D.C. (1998), Optimal smoothing for trend removal in short term electricity demand forecasting, *IEEE Transactions on Power Delivery*, Vol. 13, No. 3, August 1998.

International Atomic Energy Agency (2004), Power Reactor Information System, Reference Data Series 2, Available online: http://www.iaea.org/programmes/a2/., at 22 July 2004.

Iyer, V., Fung, C.C., and Gedeon, T. (2003), A fuzzy-neural approach to electricity load and spot-price forecasting in a deregulated electricity market, *TENCON 2003: Conference on Convergent Technologies for Asia-Pacific Region*, Vol. 4 , pp. 1479 – 1482, 15-17 Oct. 2003.

Jain, D.C. and Rao, R.C. (1994), New concepts and applications in growth phenomena, *Journal of Applied Statistics*, Vol. 21, No.3, pp. 161-190, 1994.

Jenne, C., and Catell, R. (1983), Electricity intensity in UK industry, *Energy Policy*, Vol. 11, Issue 4, pp. 369-371, 1983.

Jia, N.X., Yokoyama, R., Zhou, Y.C., and Gao, Z.Y. (2001), A flexible long-term forecasting approach based on new dynamic simulation theory – GSIM, *Electrical Power and Energy Systems*, Vol. 23, pp. 549-556, 2001.

Kandil, M.S., El-Debeiky, S.M., and Hasanien, N.E. (2001), Overview and comparison of long-term forecasting techniques for a fast developing utility: part 1, *Electric Power Systems Research,* Vol. 58, pp. 11-17, 2001.

Kermanshahi, B. (1998), Recurrent neural network for forecasting next 10 years loads of nine Japanese utilities, *Neurocomputing*, Vol. 23, pp. 125-133, 1998.

Kermanshahi, B., and Iwamiya, H. (2002), Up to 2020 load forecasting using neural nets, *International Journal of Electrical Power and Energy Systems*, Vol. 24, No. 9, pp. 789-797, 2002.

Khatib, H. (1993), Electricity in the global energy scene, *IEE Proceedings – A*, Vol. 140, No. 1, January 1993.

Khotanzad, A., Afkhami-Rohani, R., Lu, T.-L., Abaye, A., Davis, M., and Maratukulam, D.J. (1997), ANNSTLF-A neural network based electric load forecasting system, *IEEE Trans. Neural Networks*, Vol. 8, pp. 835–846, July 1997.

Kim, Y.S., Sohn, S.Y., and Yoon, C.Y. (2003), Screening test data analysis for liver disease prediction model using growth curve, *Biomedecine & Pharmacotherapy*, Vol. 57, Issue 10, pp. 482-488, December 2003.

Komprej, I., and Zunko, P. (1991), Short term load forecasting, *IEEE Electrotechnical Conference, 1991. Proceedings.,* 6th Mediterranean , Vol.2, pp.1470-1473, 22-24 May 1991.

Ku, A. (2002), The art of forecasting demand, *Global Energy Business*, March/April 2002, pp. 20-23.

Lakhani, H.G., and Bumb, B. (1978), Forecasting demand for electricity in Maryland: An econometric approach, *Technological Forecasting and Social Change*, Vol. 11, pp. 237-261, 1978.

Leach, D. (1981), Re-evaluation of the logistic curve for human populations, *Journal of the Royal Statistics Society A*, Vol. 144, pp. 94-103, 1981.

Levenbech, H., and Reuter, B.E. (1976), Forecasting trending time series with relative growth rate models, *Technometrics*, Vol. 18, pp. 261-272, 1976.

Liang, R.H., and Cheng, C.C. (2002), Short-term load forecasting by a neuro-fuzzy based approach, *International Journal of Electrical Power and Energy Systems*, Vol. 24, No. 2, pp. 103-111, 2002.

Liu, X.Q., Ang, B.W., and Goh, T.N. (1991), Forecasting of electricity consumption: A comparison between an econometric model and a neural network model, *IEEE International Conference on Neural Networks*, Vol. 2, pp. 1254–1259, 18-21 November 1991.

Ljung, G.M., and Box, G.E.P. (1978), On a measure of lack of fit in time series models, *Biometrica*, Vol. 65, pp. 297-303, 1978.

Lomi, A., and Larsen, E. (1999), Learning without experience: Strategic implications of deregulation and competition in the electricity industry, *European Management Journal*, Vol. 17, No.2, pp.151-163, 1999.

Long, J.F. (1995), Complexity, accuracy, and utility of official population projections, *Mathematical Population Studies*, Vol. 5, pp. 203-216, 1995.

Machado, G.V., Schaeffer, R., and Worrell, E. (2001), Energy and carbon embodied in the international trade of Brazil: an input-output approach, *Ecological Economics*, Vol. 39, Issue 3, pp. 409-424, 2001.

Maharajan, V. and Peterson, R.A. (1978), Innovation diffusion in a dynamic-potential adopter population, *Management Science*, Vol. 24, pp. 1589–1597, 1978.

Maharajan, V., Peterson, R.A., Jain, A.K and Malhotra, N. (1979), A new product growth model with a dynamic market potential: Long range planning, *Technological Forecasting and Social Change*, Vol. 12, pp. 51-58, 1979.

Maki, A. (2002), Changes in New Zealand consumer living standards during the period of deregulation 1984-1996, *The Economic Record*, Vol. 78, No. 243, pp. 443-450, December 2002.

Makridakis, S., and Wheelwright, S.C. (1989), *Forecasting Methods for Management*, John Wiley & Sons, Fifth Edition, 1989.

Makridakis, S., Anderson, A., Carbone, R., Fildes, R.,Hibon, M., Lewandowski, R., Newton, J., Parzen, E., and Winkler, R. (1984), *The Forecasting Accuracy of Major Time Series Methods*, Wiley, Chichester, 1984.

Makridakis, S., Wheelwright, S.C., and Hyndman, R.J. (1998), *Forecasting: Methods and Applications*, John Wiley and Sons, Inc., New York, 1998.

Mansfield, E. (1961), Technical change and the rate of imitation, *Econometrica*, Vol. 29, No. 4, pp. 741 – 765, October 1961.

Mar-Molineo (1980), Tractors in Spain: A logistic analysis, *Journal of Operational Research Society*, Vol.31, pp.141-152, 1980.

Martin, J.E. (1998), *People, Politics and Power Stations*, Second Edition, Electricity Corporation of New Zealand, PO Box 930, Wellington, New Zealand, 1998.

Martino, J.P. (2003), A review of selected recent advances in technological forecasting, *Technological Forecasting and Social Change*, Vol. 70, Issue 8, pp. 719-733, October 2003.

Masini, A., and Frankl, P. (2003), Forecasting the diffusion of photovoltaic systems in southern Europe: A learning curve approach, *Technological Forecasting and Social Change*, Vol. 70, Issue 1, pp. 39-65, January 2003.

McGovern, T., and Hicks, C. (2004), Deregulation and restructuring of the global electricity supply industry and its impact upon power plant suppliers, *International Journal of Production Economics*, Vol. 89, pp. 321-337, 2004.

Meade, N. and Islam, T. (1995), Forecasting with growth curves: An empirical comparison, *International Journal of Forecasting*, Vol. 11, Issue 2, pp. 199-215, 1995.

MED (1958-74), Ministry of Economic Development, *Annual Statistics in Relation to Electric Power Development and Operation year ended .... condensed statistics for the combined developments + operations of the NZ Electricity Department + Distributing Electrical Supply Authorities*, Wellington, A.R. Shearer, Government Printer, 1958 – 1974.

MED (2000), Ministry of Economic Development - Modelling and Statistics Unit, *New Zealand Energy Outlook to 2020*, Crown Copyright 2000, Wellington, February 2000.

MED (2002), Ministry of Economic Development, *New Zealand Energy Data File*, Crown Copyright, Wellington, July 2002.

MED_EMPG (2002), Ministry of Economic Development – Energy Markets and Policy Group (Resources and Network Branch, *Chronology of New Zealand Electricity Reforms*, July 2002. Online: Available at: http://www.med.govt.nz/ers/electric/chronology/index.html, 8 September 2003.

MED_EMPG (2001), Ministry of Economic Development – Energy Markets and Policy Group *New Zealand's Electricity Sector*, February 2001. Online: Available at: http://www.med.govt.nz/ers/electric/sector/index.html, 8 September 2003.

Methaprayoon, K. (2003), Neural network-based short term load forecasting for unit commitment scheduling, A thesis presented to the Faculty of the Graduate School in partial fulfilment of the requirements for the degree of Master of Science in Electrical Engineering, The University of Texas at Arlington, August 2003.

Meyer, P.S. and Ausubel, J.H. (1999), Carrying capacity: A model with logistically varying limits, *Technological Forecasting and Social Change*, Vol. 61, pp. 209-214, 1999.

Meyers, S., and Sathaye, J. (1989), Electricity use in the developing countries: Changes since 1970, *Energy*, Vol. 14, No. 8, pp. 435-441, 1989.

Mielnik, O., and Goldemberg, J. (2000), Converging to a common pattern of energy use in developing and industrialised countries, *Energy Policy*, Vol. 28, Issue 8, pp. 503-508, 2000.

Ministry of Energy (1982-84), *Electricity Forecasting and Planning: A Background Report to the 1982-84 Energy Plan*, Wellington, 1982 -1984 issues.

Ministry of Tourism (2004), Male', Republic of Maldives, Official Website: http://www.visitmaldives.com.mv/ 19 March 2004.

Mitchell, B.R. (1988), *British Historical Statistics*, Cambridge University Press, 1988.

Mohamed Z, Bodger, P.S. (2003), Analysis of the Logistic model for Predicting New Zealand Electricity Consumption, *Proceedings of Electricity Engineer's Association (EEA) New Zealand Conference 2003*, Christchurch, New Zealand, June 2003.

Mohamed and Bodger_1 (2004), Mohamed, Z., and Bodger, P.S. (2004), Forecasting electricity consumption in New Zealand using economic and demographic variables, *Energy (The International Journal)*, Accepted for publication, 2004.

Mohamed and Bodger_2 (2004), Mohamed, Z., and Bodger, P.S., A Comparison of Logistic and Harvey models for electricity consumption in New Zealand, *Technological Forecasting and Social Change*, Accepted for publication, ARTICLE IN PRESS, Available online at http://www.sciencedirect.com, 2004.

Mohamed and Bodger_3 (2004), Mohamed, Z., and Bodger, P.S., A Variable Asymptote Logistic (VAL) model to forecast electricity consumption, *International Journal of Computer Applications in Technology (IJCAT)*, Accepted for publication, 2004.

Mori, H., and Kobayashi, H. (1996), Optimal fuzzy inference for short-term load forecasting, *IEEE Transactions on Power Systems*, Vol. 11, No. 1, pp. 390-396, 1996.

MPND (2004), Ministry of Planning and National Development, Male' Republic of Maldives, Official Website: http://www.planning.gov.mv/ 19 March 2004.

MPND (2003), Ministry of Planning and National Development, *Statistical Year Book of Maldives 2003*, Male', Republic of Maldives, 2003.

Nagata, Y. (1997), The US/Japan comparison of energy intensity: Estimating the real gap, *Energy Policy*, Vol. 25, Nos. 7-9, pp. 683-691, 1997.

Nilsson, L.J. (1993), Energy intensity trends in 31 industrial and developing countries 1950-1988, *Energy*, Vol. 18. No. 4, pp.309-322, 1993.

Office for National Statistics (2004), Source: National Statistics website: www.statistics.gov.uk, on 20 May 2004, Crown copyright material is reproduced with the permission of the Controller of HMSO.

Oliveira, R.G., and Tolmasquim, M.T. (2004), Regulatory performance analysis case study: Britain's electricity industry, *Energy Policy*, Vol. 32, pp. 1261-1276, 2004.

Oliver, F.R. (1981), Tractors in Spain: a further logistic analysis, *Journal of the Operational Research Society*, Vol. 32, pp.499 – 502, 1981.

Pack, D.J. (1980), In defense of ARIMA modelling, *International Journal of Forecasting*, Vol. 6, pp.211-218, 1990.

Padmakumari, K., Mohandas K.P., and Thiruvengadam S. (1999), Long term distribution demand forecasting using neuro fuzzy computations, *International Journal of Electrical Power and Energy Systems*, Vol. 21, No. 5, pp. 315-22, 1999;

Park, D.C., El-Sharakawi, M.A., Marks, R.J., Atlas, L.E., and Damborg, M.J. (1991), Electric load forecasting using artificial neural networks, *IEEE Trans. Power Syst.*, Vol. 6, pp. 228-442, May 1991.

Pearl, R. (1924), *Studies in Human Biology*, Baltimore Williams & Wilkins Company, 1924.

Percebois, J., and Wright, P. (2001), Electricity consumers under the state and private sector: comparing the price performance of the French and UK electricity industries 1990-2000, *Utilities Policy*, Vol. 10, pp. 167-179, 2001.

Pflaumer, P. (1992), Forecasting US population totals with the Box-Jenkins approach, *International Journal of Forecasting*, Vol. 8, pp. 329-338, 1992.

Piras, A., Germond. A., Buchenel, B., Imhof, K., and Jaccard, Y. (1996), Heterogeneous artificial neural network for short term electrical load forecasting, *IEEE Trans. Power Syst.*, Vol. 11, pp. 397-402, Feb. 1996.

Porter, A.L., Roper, A.T., Mason, T.W., Rossini, F.A., and Banks, J. (1991), *Forecasting and Management of Technology*, John Wiley and Sons, New York, 1991.

Preez, J. and Witt, S.F. (2002), Univariate versus multivariate time series forecasting: an application to international tourism demand, *International Journal of Forecasting*, Article in Press, 2002.

Priambodo, A., and Kumar, S. (2002), Energy use and carbon dioxide emission of Indonesian small and medium scale industries, *Energy Conservation and Management*, Vol. 42, pp. 1335-1348, 2002.

Quenouille, M.H. (1949), The joint distribution of serial correlation coefficients, *Annals of Mathematical Statistics*, Vol. 20, pp. 561-71, 1949.

Rajan, M., and Jain, V.K. (1999), Modelling of electrical energy consumption in Delhi, *Energy*, Vol. 24, pp. 351-361, 1999.

Ranaweera, D.K, Hubele, N.F, and Karady, G.G. (1996), Fuzzy Logic for shot to term load forecasting, *International Journal of Electrical Power and Energy Systems*, Vol. 18, No. 4, pp. 215-222, 1996.

Reddy, B.S., and Balachandra, P. (2003), Integrated energy-environment-policy analysis – a case study of India, *Utilities Policy*, Vol. 11, pp. 59-73, 2003.

Saab, S., Badr, E. and Nasr, G. (2001), Univariate modelling and forecasting of energy consumption: the case of electricity in Lebanon, *Energy*, Vol. 26, Issue 1, pp. 1-14, January 2001.

Sailer, D.J. (2001), Relating residential and commercial sector electricity loads to climate – evaluating state level sensitivities and vulnerabilities, *Energy*, Vol. 26, pp. 645-657, 2001.

Satish, B., Swarup, K.S., Srinivas, S., and Rao, H., (2004), A., Effect of temperature on short term load forecasting using an integrated ANN, *Electric Power Systems Research*, Vol. 72, Issue 1, , pp. 95-101, 15 November 2004.

Schaeffer, R., and de Sa, A.L. (1996), The embodiment of carbon associated with Brazilian imports and exports, *Energy Conversion and Management*, Vol. 37, Issue 6-8, pp. 955-960, 1996.

Schfer, A. (2005), Structural change in energy use, *Energy Policy*, Vol. 33, Issue 4, pp. 429-437, March 2005.

Schipper, L., Meyers, S., and Ketoff, A. (1986), Energy use in the service sector: An international perspective, *Energy Policy*, Vol. 14, Issue 3, pp. 201-218, 1986.

Schnaars, S.P. (1984), Situational factors affecting forecast accuracy, *Journal of Marketing Research*, Vol. 21, pp. 290-297, 1984.

Sharif, M.N., and Islam, M.N. (1980), The Weibull distribution as a general model for forecasting technological change, *Technological Forecasting and Social Change*, Vol. 18, pp. 247-256, 1980.

Sharif, M.N., and Ramanathan, K. (1981), Binomial innovation diffusion models with dynamic potential adopter population, *Technological Forecasting and Social Change*, Vol. 20, pp. 63-87, 1981.

Sharif, M.N., and Ramanathan, K. (1984), Temporal models for innovation diffusion, *IEEE Transactions on Engineering Management*, Vol. 31, pp. 78-86, 1984.

Sharp, J.A., and Price, H.R. (1990), Experience curve models in the electricity supply industry, *International Journal of Forecasting*, Vol. 6, pp. 531-540, 1990.

Shiu, A., and Lam, P. (2004), Electricity consumption and economic growth in China, *Energy Policy*, Vol. 32, pp. 47-54, 2004.

Sinclair Knight Merz and Centre for Advanced Engineering (2000), Electricity Supply and Demand to 2015, Fifth Edition, University of Canterbury, April 2000, New Zealand.

Skiadas, C.H, Papayannakis L.L., and Mourelatos, A. G. (1993), An attempt to improve forecasting ability of growth functions: The Greek electric system, *Technological Forecasting and Social Change*, Vol. 44, pp. 391-404, 1993.

Smith, M.C., and Sincich, T. (1990), The relationship between the length of the base period and population forecast errors, *Journal of the American Statistical Association*, Vol. 85, pp. 367-375, 1990.

Smith, S.K. (1997), Further thoughts on simplicity and complexity in population projection models, *International Journal of Forecasting*, Vol. 13, pp. 557-565, 1997.

Srinivasan, D., Tan, S.S., Cheng, C.S., and Chan. E.K. (1999), Parallel neural network-fuzzy system strategy for short-term load forecasting: System implementation and performance evaluation, *IEEE Trans. Power Syst.*, Vol. 14, pp. 1100–1106, Aug. 1999.

Stapleton, E. (1978), The normal distribution as a model for technological substitution, *Technological Forecasting and Social Change*, Vol. 8, pp. 325 – 334, 1978.

Statistics New Zealand (2002), New Zealand, Web page: http://www.stats.govt.nz, June 2002.

STELCO (2004), State Electric Company Limited, Male, Maldives, Website: http://www.stelco.com.mv on 4 September 2004.

Subrahmanya, M.H.B. (2004), Energy intensity and economic performance of small scale bricks and foundry clusters in India: does energy intensity matter?, *Energy Policy*, ARTICLE IN PRESS, 2004.

Sun, J.W., and Kuntsi, E. (2004), Environmental impact of energy use in Bangladesh, India, Pakistan and Thailand, *Global Environmental Change*, Vol. 14, pp.161-169, 2004.

Sun, J.W. (1998), The decrease in the difference of energy intensities between OECD countries from 1971 to 1998, *Energy Policy*, Vol. 30, Issue 8, pp. 631-635, 2002.

Sun, J.W. (2003), Three types of decline in energy intensity – An explanation for the decline of energy intensity in some developing countries, *Energy Policy*, Vol. 31, pp. 519-526, 2003.

Tay, H. S. (1985), *Forecasting New Zealand Electricity Consumption: A Logistic Initiative*, A report presented for the degree of Master of Engineering, University of Canterbury, Christchurch, New Zealand, 1985.

Theriault, L., and Sahi, R. (1997), Energy intensity in the manufacturing sector: Canadian and international perspective, *Energy Policy*, Vol. 25, Nos. 7-9, pp. 773-779, 1997.

Tigert, D., and Farivar, F. (1981), The Bass new product growth model: A sensitivity analysis for a high technology product, *Journal of Marketing*, Vol. 45, pp. 81-90, 1981.

Tingyan, X. (1990), A combined growth model for trend forecasts, *Technological Forecasting and Social Change*, Vol. 38, pp. 175-186, 1990.

Tunc, M., Camdali, U., Parmaksizoglu, C. (2004), Comparison of Turkey's electrical energy consumption and production with some European countries and optimisation of future electrical power supply investments in Turkey, *Energy Policy*, ARTICLE IN PRESS, 2004.

Turner, B. (2005), *The Statesman's Year-book*, 141st ed, St. Martin's Press, New York, 2005.

Twiss, B.C. (1992), *Forecasting for Technologists and Engineers: A practical guide for better decisions*, Peter Peregrinus Ltd., London, United Kingdom, 1992.

Unander, F., Ettestol, I., Ting, M., and Schipper, L. (2004), Residential energy use: An international perspective on long-term trends in Denmark, Norway and Sweden, *Energy Policy*, Vol. 32, pp. 1395-1404, 2004.

Vellasco, M.M.B.R., Pacheco, M.A.C., Neto, L.S.R., Souza, F.J. (2004), Electric load forecasting: evaluating the novel hierarchical neuro-fuzzy BSP model, *International Journal of Electrical Power and Energy Systems*, Vol. 26, No. 2, pp. 131-142, 2004.

Whitaker, J. (2005), *Whitaker's Almanack*, 137th Ed, J. Whitaker & Sons, London.

Wong, Y.K., and Rad, A.B. (1998), Gauss-Markov models for forecasting and risk evaluation, Proc. *EMPD'98 IEEE International Energy Management and Delivery Conference 1998*, Vol.1, pp. 287-292, 3-5 March 1998.

Worrell, E., Price, L., Martin, N., Farla, J., and Schaeffer, R. (1997), Energy intensity in the iron and steel industry: A comparison of physical and economic indicators, *Energy Policy*, Vol. 25. Nos. 7-9, pp. 727-744, 1997.

Wright, J.W. (2003), *2004 The New York Times Almanac*, The New York Times Company, New York.

Yalcinoz, T., and Eminoglu, U. (2005), Short term and medium term power distribution load forecasting by neural networks, *Energy Conservation and Management*, Vol. 46, pp. 1393-1405, 2005.

Yan, Y.Y. (1998), Climate and residential electricity consumption in Hong Kong, *Energy*, Vol. 23, No. 1, pp. 17-20, 1998.

Young, P. (1993), Technological growth curves: A competition of forecasting models, *Technological Forecasting and Social Change*, Vol. 44, pp. 375-389, 1993.

Zhang, Z.X. (2003), Why did the energy intensity fall in China's industrial sector in the 1990's? The relative importance of structural change and intensity change, *Energy Economics*, Vol. 25, pp. 625-638, 2003.

APPENDIX A

DATA FOR MALDIVES, NEW ZEALAND, UNITED STATES AND UNITED KINGDOM

A1. MALE', MALDIVES

Year	Electricity Consumption (GWh)			GDP[1] (millions Rufiyya)	Population[2]
	Domestic	Non-Domestic	Total		
1980	1.153	0.831	1.984	799.20	156803
1981	1.312	0.878	2.19	1003.20	161460
1982	2.345	2.709	5.054	1207.20	166117
1983	3.239	3.119	6.358	1411.20	170774
1984	3.757	3.624	7.381	1615.20	175431
1985	4.396	4.236	8.632	1864.20	180088
1986	5.374	4.936	10.31	2038.70	186713
1987	6.403	5.817	12.22	2218.70	193338
1988	7.471	6.918	14.389	2412.40	199963
1989	8.236	7.938	16.174	2637.40	206588
1990	10.823	9.43	20.253	3084.50	213215
1991	12.013	11.615	23.628	3297.10	219535
1992	13.538	13.749	27.287	3510.30	225855
1993	18.806	15.744	34.55	3700.50	234010
1994	17.942	18.798	36.74	3978.20	240255
1995	20.661	23.521	44.182	4271.60	244827
1996	22.7	24.27	46.97	4659.70	250144
1997	25.431	26.638	52.069	5144.60	255460
1998	28.192	31.14	59.332	5648.20	260777
1999	30.109	34.565	64.674	6056.60	266093
2000	33.91	39.774	73.684	6345.50	271410
2001	38.364	43.782	82.146	6564.40	275975

[1] GDP for 1980-1982 estimated

[2] Estimated mid-year populations from 1980-1992 based on actual counts of 1977, 1985 & 1990

A2. NEW ZEALAND

Year	Electricity Consumption (GWh)			Real GDP	Population	Real Price
	Domestic	Non-Domestic	Total	(millions $NZ)		(cents $NZ/kWh)
1943	900	838	1738	-	1642000	-
1944	942	861	1803	-	1676300	-
1945	1024	866	1890	-	1727800	-
1946	1123	875	1998	-	1781200	-
1947	1141	895	2036	-	1817500	-
1948	1307	971	2278	-	1853900	-
1949	1376	1028	2404	-	1892100	-
1950	1398	1048	2446	-	1927700	-
1951	1612	1121	2733	-	1970500	-
1952	1692	1154	2846	-	2024600	-
1953	1945	1283	3228	-	2074700	-
1954	2142	1399	3541	-	2118400	-
1955	2316	1560	3876	-	2164800	-
1956	2367	1698	4065	-	2209200	-
1957	2760	1893	4653	-	2262800	-
1958	2741	1961	4702	-	2316000	-
1959	3122	2152	5274	-	2359700	-
1960	3360	2324	5684	-	2403600	20.4
1961	3656	2513	6169	-	2461300	19.8
1962	3920	2764	6684	-	2515800	19.3
1963	4408	3169	7577	39302	2566900	18.5
1964	4715	3474	8189	41704	2617000	17.9
1965	5192	3813	9005	44245	2663800	17.2
1966	5560	4042	9602	45923	2711300	16.5
1967	5697	4196	9893	45527	2745000	14.4
1968	5992	4468	10460	46497	2773000	14.8
1969	6187	4886	11073	48845	2804000	13.9
1970	6454	5300	11754	50653	2852100	12.4
1971	6811	6301	13112	51942	2898500	11.2
1972	7389	7642	15031	54244	2959700	11.2
1973	7440	8508	15948	58136	3024900	9.1
1974	7554	8719	16273	60479	3091900	8
1975	8403	9248	17651	61497	3143700	7
1976	8398	9905	18303	61586	3163400	8.6
1977	8314	10595	18909	59992	3166400	10.4
1978	8181	10707	18888	60115	3165200	10
1979	7909	11130	19039	61649	3163900	11.9
1980	8035	11505	19540	62312	3176400	11.3
1981	8265	11840	20105	65374	3194500	10.6
1982	8733	12638	21371	65793	3226800	11.1
1983	8981	14047	23028	67595	3264800	10.4
1984	8998	14996	23994	70929	3293000	9.2
1985	9080	15196	24276	71476	3303100	10.1
1986	9424	15925	25349	72973	3350000	9.7
1987	9423	16382	25805	73275	3342100	10.2
1988	9510	17187	26697	72989	3345200	10.3
1989	9824	17486	27310	73607	3369800	9.7
1990	10264	17555	27819	73174	3410400	9.5
1991	10474	18134	28608	72278	3498100	9.6
1992	10124	17662	27786	73124	3534400	9.8
1993	10256	18972	29228	77740	3579900	9.7
1994	10416	19509	29925	81920	3630400	9.3
1995	10584	19937	30521	85016	3688700	9.6
1996	10959	20301	31260	87211	3743400	9.8
1997	10824	20565	31389	88949	3781300	10.1
1998	11089	20940	32029	88872	3805600	9.9
1999	11329	22550	33879	92970	3825800	9.5

A3. UNITED STATES OF AMERICA

Year	Electricity Consumption (TWh)			GDP	Population	Electricity Price
	Domestic	Non-Domestic	Total	(billions US$)	(millions)	(cents(US$)/kWh)
1949	66.79	187.72	254.51	1550.9	148.7	-
1950	72.20	219.24	291.44	1686.6	151.3	-
1951	83.09	247.19	330.28	1815.1	154	-
1952	93.54	262.62	356.16	1887.3	156.4	-
1953	104.15	292.07	396.22	1973.9	159	-
1954	116.23	307.93	424.16	1960.5	161.9	-
1955	128.40	368.35	496.75	2099.5	165.1	-
1956	143.48	402.80	546.28	2141.1	168.1	-
1957	156.72	419.10	575.82	2183.9	171.2	-
1958	169.49	418.37	587.86	2162.8	174.1	-
1959	184.54	462.35	646.89	2319	177.1	-
1960	201.46	486.61	688.07	2376.7	179.3	8.1
1961	214.44	507.51	721.95	2432	183	8
1962	232.80	544.80	777.60	2578.9	185.7	7.9
1963	250.75	581.86	832.61	2690.4	188.4	7.8
1964	271.84	624.22	896.06	2846.5	191.1	7.3
1965	291.01	662.78	953.79	3028.5	193.5	7.2
1966	316.89	718.25	1035.10	3227.5	195.5	7
1967	340.11	759.11	1099.20	3308.3	197.4	6.7
1968	381.57	821.30	1202.90	3466.1	199.3	6.1
1969	426.74	887.09	1313.80	3571.4	201.3	5.8
1970	466.29	926.01	1392.30	3578	203.3	5.8
1971	499.53	970.01	1469.50	3697.7	206.8	5.9
1972	538.61	1056.60	1595.20	3898.4	209.3	6
1973	579.23	1133.70	1712.90	4123.4	211.4	6
1974	578.18	1127.70	1705.90	4099.00	213.3	6.8
1975	588.14	1158.90	1747.10	4084.4	215.5	7.2
1976	606.45	1248.80	1855.30	4311.7	217.6	7.3
1977	645.24	1303.10	1948.40	4511.8	219.8	7.6
1978	674.47	1343.50	2017.90	4760.6	222.1	7.7
1979	682.82	1388.30	2071.10	4912.1	224.6	7.7
1980	717.50	1376.90	2094.40	4900.9	226.5	8.2
1981	722.27	1424.80	2147.10	5021	229.5	8.8
1982	729.52	1356.90	2086.40	4919.3	231.7	9.2
1983	750.95	1400.00	2150.90	5132.3	233.8	9.2
1984	780.09	1505.70	2285.80	5505.2	235.8	8.75
1985	793.93	1530.00	2324.00	5717.1	237.9	8.74
1986	819.09	1549.70	2368.80	5912.4	240.1	8.55
1987	850.41	1606.90	2457.30	6113.3	242.3	8.21
1988	892.87	1685.20	2578.10	6368.4	244.5	7.92
1989	905.52	1849.40	2754.90	6591.8	246.8	7.75
1990	924.02	1902.60	2826.60	6707.9	248.8	7.59
1991	955.42	1924.60	2880.00	6676.4	253	7.53
1992	935.94	1949.70	2885.60	6880	256.5	7.43
1993	994.78	1994.20	2989.00	7062.6	259.9	7.37
1994	1008.50	2060.20	3068.70	7347.7	263.1	7.2
1995	1042.50	2114.80	3157.30	7543.8	266.3	7.02
1996	1082.50	2164.50	3247.00	7813.2	269.4	6.86
1997	1075.90	2218.20	3294.00	8159.5	272.6	6.72
1998	1130.10	2295.00	3425.10	8508.9	275.9	6.53
1999	1144.90	2349.70	3494.60	8859	279	6.34
2000	1192.50	2412.20	3604.70	9191.4	281.4	6.37
2001	1202.70	2351.10	3553.80	9214.5	285.3	6.69
2002	1268.20	2391.80	3660.00	9439.9	288.4	6.5

A4. UNITED KINGDOM

Year	Electricity Consumption (TWh)			GDP	Population
	Domestic	Non-Domestic	Total	(billions pounds)	(thousands)
1965	57.23	97.48	154.71	-	-
1966	59.81	100.84	160.65	-	-
1967	62.35	103.40	165.75	-	-
1968	66.66	111.54	178.20	-	-
1969	72.19	117.67	189.86	-	-
1970	77.04	121.96	199.00	418	55632
1971	80.67	123.89	204.56	426.7	55907
1972	86.89	124.66	211.55	442.2	56082
1973	91.30	135.18	226.48	474.2	56218
1974	92.63	127.01	219.64	466.70	56232
1975	89.21	129.86	219.07	464.1	56213
1976	85.12	136.88	222.00	477	56202
1977	85.90	140.90	226.80	487.9	56173
1978	85.80	145.62	231.42	504.2	56160
1979	89.67	152.33	242.00	517.4	56218
1980	86.11	145.00	231.11	506.5	56303
1981	84.44	142.77	227.21	499.1	56357.5
1982	82.79	140.03	222.82	509	56298.2
1983	82.95	143.14	226.09	527.4	56327.7
1984	83.90	147.06	230.96	540.7	56422.8
1985	88.23	153.62	241.85	560.3	56567.4
1986	91.83	167.99	259.82	582.4	56699
1987	93.25	175.13	268.38	608.6	56850
1988	92.36	182.14	274.50	640.2	56970.1
1989	92.27	187.13	279.40	654	57132.7
1990	93.79	190.63	284.42	659.2	57285.4
1991	98.10	192.74	290.84	650.1	57471.9
1992	99.48	191.97	291.45	651.6	57593
1993	100.46	195.29	295.75	667.8	57700.1
1994	101.41	191.42	292.83	698.9	57825.3
1995	102.21	201.71	303.92	719.2	57958.2
1996	107.51	212.27	319.78	738.05	58075.8
1997	104.46	216.61	321.07	763.46	58204.3
1998	109.41	215.94	325.35	785.78	58348.6
1999	110.31	221.74	332.05	804.71	58534.6
2000	111.84	228.46	340.30	829.52	58654.5
2001	115.34	227.44	342.78	847.02	58836.7
2002	114.54	229.30	343.83	862.27	59231.9

Note:- Sources of all these country data are described in the relevant text (Chapters 6 to 9).

APPENDIX B

DATA FOR REGIONS AND WORLD TOTAL

B1. ELECTRICITY CONSUMPTION

Year	Electricity Consumption (TWh)								
	NA	CSA	WE	IA	EEFSU	ME	AF	DA	Total
1980	2470	287	1645	614	1538	109	176	577	7416
1981	2536	293	1648	619	1496	120	186	607	7507
1982	2484	311	1651	628	1610	141	192	650	7668
1983	2562	331	1703	661	1669	155	200	699	7980
1984	2724	356	1785	698	1756	173	218	760	8471
1985	2786	377	1865	724	1814	188	234	824	8812
1986	2849	411	1903	735	1795	196	246	898	9034
1987	2959	428	1960	789	1862	209	258	984	9448
1988	3105	446	1996	828	1901	238	266	1084	9864
1989	3305	453	2045	871	1934	248	277	1174	10305
1990	3369	462	2067	931	1906	263	286	1259	10543
1991	3432	482	2104	960	1861	268	292	1364	10764
1992	3446	499	2118	968	1741	297	294	1463	10826
1993	3563	529	2128	982	1652	325	305	1592	11077
1994	3656	547	2159	1038	1511	353	317	1756	11336
1995	3758	584	2211	1067	1519	379	328	1901	11747
1996	3869	616	2267	1090	1511	405	341	2016	12114
1997	3932	649	2292	1123	1487	435	357	2155	12430
1998	4065	674	2364	1135	1463	469	362	2229	12761
1999	4158	694	2405	1144	1463	489	377	2339	13068
2000	4297	727	2485	1138	1499	525	394	2542	13606
2001	4247	714	2549	1136	1520	547	410	2711	13833
2002	4337	734	2553	1202	1544	574	422	2914	14280

(NA = North America, CSA = Central and South America, WE = Western Europe, EEFSU = Eastern Europe and Former Soviet Union, ME = Middle East, AF = Africa, DA = Developing Asia)

B2. GROSS DOMESTIC PRODUCT (GDP)

Year	GDP(billions of 1995 US Dollars)								
	NA	CSA	WE	IA	EEFSU	ME	AF	DA	Total
1980	5435	1052	6526	3557	222	418	464	1022	18695
1981	5587	1027	6532	3685	210	417	462	1085	19006
1982	5472	1017	6581	3793	208	410	473	1143	19097
1983	5686	1002	6691	3890	218	430	468	1226	19610
1984	6086	1044	6853	4061	228	443	476	1315	20506
1985	6320	1073	7035	4262	235	446	490	1390	21250
1986	6520	1141	7226	4373	337	439	489	1497	22022
1987	6741	1182	7409	4556	342	455	488	1614	22787
1988	7019	1187	7706	4832	350	462	511	1751	23818
1989	7262	1196	7980	5056	348	493	533	1854	24722
1990	7387	1205	8233	5288	318	529	544	1965	25469
1991	7358	1246	8553	5455	270	550	550	2088	26070
1992	7571	1282	8652	5509	855	590	544	2252	27255
1993	7768	1340	8628	5546	859	617	539	2426	27722
1994	8087	1411	8862	5616	798	621	548	2635	28578
1995	8276	1457	9069	5712	793	650	562	2850	29370
1996	8565	1505	9213	5913	795	683	591	3060	30326
1997	8949	1577	9444	6020	813	711	611	3235	31358
1998	9330	1602	9704	5974	810	728	630	3248	32026
1999	9715	1595	10006	6004	829	727	649	3465	32991
2000	10096	1643	10350	6173	879	769	673	3707	34290
2001	10138	1651	10510	6210	918	767	697	3840	34729
2002	10363	1636	10613	6209	946	794	714	4030	35305

(NA = North America, CSA = Central and South America, WE = Western Europe, EEFSU = Eastern Europe and Former Soviet Union, ME = Middle East, AF = Africa, DA = Developing Asia)

B3. POPULATION

Year	Population (millions)								
	NA	CSA	WE	IA	EEFSU	ME	AF	DA	Total
1980	319	291	366	135	383	136	465	2320	4415
1981	324	297	367	136	386	141	479	2366	4495
1982	328	303	368	137	389	145	492	2412	4574
1983	331	308	368	138	392	150	507	2456	4652
1984	335	313	369	139	396	156	522	2502	4732
1985	339	319	369	140	399	162	537	2548	4812
1986	343	326	370	141	402	167	552	2604	4904
1987	347	332	371	142	405	171	565	2654	4988
1988	351	339	372	142	406	175	580	2704	5071
1989	356	348	374	143	409	180	598	2753	5160
1990	360	354	376	144	414	185	612	2802	5246
1991	365	364	377	145	415	196	636	2862	5361
1992	370	371	379	145	414	201	655	2908	5443
1993	374	377	381	146	414	206	672	2954	5524
1994	379	383	382	147	413	211	692	3000	5607
1995	383	390	384	147	413	215	710	3046	5688
1996	388	396	385	148	413	220	727	3092	5768
1997	392	402	386	148	412	225	744	3138	5848
1998	396	409	387	149	412	229	761	3184	5927
1999	401	415	388	149	411	234	778	3229	6005
2000	412	421	389	150	410	239	795	3272	6089
2001	417	428	390	150	410	244	813	3315	6166
2002	421	434	391	151	409	249	831	3357	6243

(NA = North America, CSA = Central and South America, WE = Western Europe, EEFSU = Eastern Europe and Former Soviet Union, ME = Middle East, AF = Africa, DA = Developing Asia)

Note:- Sources of all these regional data are described in the relevant text (Chapter 10).